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A schematic model for molecular affinity and binding with Ising variables

Fabrice Thalmann¹

Institut Charles Sadron, Université de Strasbourg, CNRS UPR 22, 23 rue du Loess, BP 84047, F-67034 Strasbourg Cedex, France

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Abstract. After discussing the relevance of statistical physics in molecular recognition processes, we present a schematic model for ligand-receptor association based on an Ising chain. We discuss the possible behaviors of the affinity when the stiffness of the ligand increases. We also consider the case of flexible receptors. A variety of interesting behaviors is obtained, including some affinity modulation upon bond hardening or softening. The affinity of a ligand for its receptor is shown to depend on the details of their rigidity profile, and we question the possibility of encoding information in the rigidities as well as in the shape. An exhaustive study of the selectivity of patterns with length $n < 8$ is carried on. Connection with other spin models, in particular spin glasses is mentioned in conclusion.

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1 Introduction

Molecular biology and biochemistry differ from chemistry and physics by the very high specificity of the interactions and the processes that they aim at describing. Words like *functions* or *shapes* are used instead of *molecules*, *atoms*, *forces* or *fields*. These biomolecules are perceived as capable of processing information (mutual recognition) and performing dedicated actions (switches or catalytic reactions). It takes only two orders of magnitude in size, from 0.1 nm to 10 nm, to abandon a world of thermal chaos and vibrations, and to enter a world of dedicated agents and reliable procedures [1].

It was suggested by E. Fisher that selective interaction and binding between molecules were primarily a consequence of their complementary shapes, which has since been known as the lock and key paradigm. These specific interactions between highly complementary moieties accounts for the specialized and efficient action of enzymes and often explains how drugs work at the molecular level. The lock and key paradigm was then extended to include final conformational changes that may happen upon binding, a mechanism known as induced fit [2]. Since a receptor and its ligand have two complementary shapes, any structural change results in decreasing the binding properties of the pair.

The tremendous increase of known 3d molecular structures (NMR and X-ray scattering) [3,4] and the ever-growing computing capacities has made of the search for complementary ligand-receptor interaction a very intense and competitive research field. Numerical approaches ba-

sed on the lock and key principle are commonly known as docking algorithms. The issue of these strategies depend on how successfully are Coulombic forces, hydrogen bonding, solvation properties, electronic densities... accounted for [5,6].

As the size of the interacting bodies increases, it is natural to question whether statistical physics still plays a role in these highly optimized recognition processes. In cells, most molecular interactions are subtly balanced in order to achieve reversibility and to prevent the occurrence of irreversible aggregation. Entropic contributions may help to achieve this balance.

One of the current goal of computational biochemistry, still out of reach, is to predict realistic ligand binding stabilization energies with an accuracy of about 1 kcal.mol^{-1} ($1.6 k_B T$), compared with experimental measurements [7]. The quenching of conformational degrees of freedom upon binding, and the subsequent entropic changes must be accounted for when computing thermodynamical association constants with such accuracy.

The immune system provides unrivaled cases of specific mutual recognition. For instance, antibodies are specialized proteins which recognize and bind in an extremely specific and accurate manner to foreign bodies invading a living organism. A recent bioinformatic study of interactions between T-cells and the major histocompatibility complex (MHC) supports the view that selective interactions between peptides may owe more to a delicate balance among many weak additive interactions, rather than to a strong complementary and exclusive mutual binding [8].

Also striking is the phenomenon of allostery. Some proteins have their function subordinated to the presence of an effector. An historically famous example is the transcription regulation of *Lac*-operon, for which it was demonstrated by Monod and Jacob that the fabrication of the lactose digesting enzymes in *e.coli* was conditioned to the presence of a significant amount of lactose in the environment of the bacteria [9]. Modern biology teaches us that in the absence of lactose, the protein *Lac*-repressor binds to a stretch of dna, and prevents the expression of the genes downstream. When lactose molecules bind to *Lac*-repressor, the protein shape changes, and it loses its ability of binding dna, enabling the expression of the genes under its control. The dna and lactose binding sites are located on distinct regions of the repressor protein, suggesting an *action at distance* caused by the presence of lactose molecules. Recently, the idea of a simple conformational change of allosteric molecules has been challenged. By studying a schematic mechanical model of *Lac*-repressor, R. Hawkins and T.C.B MacLeish estimated the contribution of internal, vibrational degrees of freedom, *i.e.* a change in protein stiffness induced by the ligand [10]. They concluded that positive or negative binding entropy changes $\Delta\Delta S$ were associated to changes (hardening or softening) in the effective spring constants used in their mechanical model of repressor proteins. It is precisely this idea of stiffness and entropic modulation of the binding site efficiency that motivates the present work.

There is, as a matter of fact, a deep and formal connection between statistical physics, recognition, binding, and information theory. When a ligand binds selectively to a patterned substrate, it accomplishes some kind of *decoding* and reads a piece of information conveyed by its target, the more conspicuous case being the association of complementary base pairs in dna-dna or dna-rna duplexes which is the cornerstone of genetic information processing. In the following Sections, we intend to show that a simple Ising spin chain can be turned into an elementary model for the binding of a ligand molecule onto a patterned receptor, in the limit where both thermal fluctuations and internal entropic degrees of freedom are relevant. Within this framework, one can tune the interactions between ligand and binding site, as well as the internal stiffness of the ligand, and we also consider flexible binding sites. The binary nature of the receptors makes them natural information carriers. After defining the affinity and selectivity of a ligand for its receptor in this situation, we discuss how much dependent are the affinities and selectivities on the stiffness parameters. Then, we proceed by giving examples of non monotonic behaviors of the affinities with increasing stiffnesses. We exhibit a case of decreased affinity upon local stiffening of the ligand, reminiscent from Hawkins and McLeish results. We show that there are affinity biases between receptors with similar shapes but different local rigidities. We finally perform an exhaustive comparison of all pairs of patterns up to a length of 8 monomers, and discuss their intrinsic ability to reliably encode information, which is found to decrease with their length. In the following sections, the word receptor will be used with the same

meaning as “binding site”, *i.e.* an object the size of the ligand that binds to it. This linguistic shortcut must not occult the fact that in many realistic cases, the receptor is a much bigger object than the ligand, and the binding site only constitutes a subpart of it. This schematic model does not pretend to accurately describe a realistic experimental situation. However, despite its simplicity, it already displays a fairly rich phenomenology which may find a counterpart in some real cases.

Using Ising-like models for modeling selective binding is not a new proposal. Indeed, Schmid, Behringer and coworkers introduced and performed intensive statistical studies of models with very similar Hamiltonians [11–13]. Their model describe the contact between hydrophobic and polar patches belonging to too opposite and complementary binding sites, and is presented as a coarse-grained approach to hydrophilic–hydrophobic interactions that are central to both protein folding and protein-protein interactions. Their spin variables describe the contact between the two rigid moieties and account for short range local rearrangements of the coarse-grained residues. A coupling J between “spin variables” is interpreted as a cooperativity property, while we associate ours to a stiffness parameter. They model 2d small rectangular patches while we discuss more schematic 1d interacting chains; our attempt to encode information in the stiffness pattern in addition to the spatial shape is not found in their work. The model introduced in Section 3 is similar to their approach, but the general approach of Section 4 is original.

2 Statistical physics of surface-bound receptors binding

Let us consider a number of ligands \mathcal{L} in contact with a single binding site \mathcal{M} linked to a rigid surface. A balance is reached resulting in an equilibrium association constant $\mathcal{K}_{\mathcal{L},\mathcal{M}}^a$ for the exchange:



from which the probability $p_{\mathcal{L},\mathcal{M}}$ of observing a ligand bound to \mathcal{M} obeys:

$$\mathcal{K}_{\mathcal{L},\mathcal{M}}^a \frac{[\mathcal{L}_{\text{free}}]}{C^0} (1 - p_{\mathcal{L},\mathcal{M}}) = p_{\mathcal{L},\mathcal{M}}, \quad (2)$$

with brackets $[\cdot]$ denoting molar concentrations, and C^0 a molar standard reference concentration, making the equilibrium association constant dimensionless, for instance $C^0 = 1\text{mol.L}^{-3}$. This is a generalization of the law of mass action that one would write for the complexation equilibrium of two species \mathcal{L}, \mathcal{M} in solution.

$$\mathcal{K}_{\mathcal{L},\mathcal{M}}^a [\mathcal{L}_{\text{free}}] \cdot [\mathcal{M}_{\text{free}}] = [\mathcal{L} \cdot \mathcal{M}_{\text{bound}}] \cdot C^0. \quad (3)$$

The equilibrium constant depends a lot on the solvation (hydration) of \mathcal{L} and \mathcal{M} , the ionic content of the solution and all the details of close range interactions between species.

As our current goal is to emphasize the role of the internal degrees of freedom of \mathcal{L} , we disregard all solvent related interactions by making a kind of ideal solution assumption, and considering that all ligand-receptor interactions are short ranged. This assumption on the solvent is equivalent to saying that all bound and unbound conformations of the ligand receptor pair have the same solvation free-energy. The mutual affinity of such a pair comes entirely from shape and stiffness considerations.

It becomes possible to express the equilibrium constant $\mathcal{K}_{\mathcal{L},\mathcal{M}}^a$ as a partition function ratio :

$$\mathcal{K}_{\mathcal{L},\mathcal{M}}^a = \frac{N_A v}{8\pi^2 V^0} \frac{Z_{\mathcal{L}\cdot\mathcal{M}\text{bound}}}{Z_{\mathcal{L}\text{free}} Z_{\mathcal{M}\text{free}}}. \quad (4)$$

$$= \frac{N_A v}{8\pi^2 V^0} \mathcal{C}_{\mathcal{L},\mathcal{M}}^a \quad (5)$$

Equation (4) is a particular instance of the equilibrium association constant derived and presented as eq. (13) in ref. [14]. N_A is the Avogadro number and V^0 is the volume occupied by one mole in the reference concentration state C^0 . $Z_{\mathcal{L}\text{free}}$ stands for the Boltzmann-Gibbs sum over all the internal conformations of \mathcal{L} , with fixed orientation and center of mass. $Z_{\mathcal{M}\text{free}}$ is a similar configuration integral over the internal conformations of \mathcal{M} when \mathcal{L} and \mathcal{M} are apart and not interacting. We assume that the configuration integral of the bound complex $\mathcal{L}\cdot\mathcal{M}$ reduces to a product $v Z_{\mathcal{L}\cdot\mathcal{M}\text{bound}}$, where $Z_{\mathcal{L}\cdot\mathcal{M}\text{bound}}$ represents the sum over all internal configurations of \mathcal{L} in contact with \mathcal{M} (with fixed centers of mass and orientations) and the volume v corresponds to all the positions of the center of mass of the ligand \mathcal{L} relative to the receptor \mathcal{M} that are considered as forming a bound state. In the context of bimolecular associations, v should range up to a few angstrom cube (10^{-30} m^3). Note that for rigid receptors $Z_{\mathcal{M}\text{free}}$ equals 1 by construction.

The association constant is obtained by setting $p_{\mathcal{L},\mathcal{M}} = 1/2$ in equation (2). One can then argue that the partition sum per free ligand

$$\frac{8\pi^2}{[\mathcal{L}\text{free}] N_A} Z_{\mathcal{L}\text{free}} Z_{\mathcal{M}\text{free}} \quad (6)$$

equals the partition sum of the bound complex

$$v Z_{\mathcal{L}\cdot\mathcal{M},\text{bound}}. \quad (7)$$

In writing these expressions, we neglected the specific volume change occurring during the binding process. In other words, we assume that the Gibbs ΔG and Helmholtz ΔF thermodynamic quantities coincide.

Equation (4) links the thermodynamical affinity constant that can be experimentally determined and the configuration integrals $Z_{\mathcal{L}\cdot\mathcal{M},\text{bound}}$, $Z_{\mathcal{L}\text{free}}$ and $Z_{\mathcal{M}\text{free}}$ that are the main focus of this work. Equation (4) can be also written as:

$$\Delta G^0 \simeq \Delta F^0 = \langle \Delta U \rangle - T \Delta S_c, \quad (8)$$

with $\Delta F^{(0)} = -k_B T \ln(\mathcal{K}_{\mathcal{L},\mathcal{M}}^a)$ and where $\langle \Delta U \rangle$ designates the average enthalpic change of moieties \mathcal{L} and \mathcal{M}

upon binding, caused by their change in conformation and mutual interaction, while ΔS_c represents the corresponding change in configurational entropy. This expression stands a particular case of

$$\Delta G^0 = \langle \Delta U \rangle + \langle \Delta W \rangle - T \Delta S_c, \quad (9)$$

demonstrated in refs. [7,14,15], where $\langle \Delta W \rangle$ accounts for the contribution of an explicit solvent to the formation of the ligand receptor pair. In aqueous solutions, both hydrogen bonding and hydration forces originate from specific interaction with the solvent. Strictly speaking, solvent mediated interactions are associated with $\langle \Delta W \rangle$ in eq. (9). However, it is to some extent possible to take them into account by means of an effective hamiltonian and treat these interactions as if they were part of the direct interaction term $\langle \Delta U \rangle$.

We define the **affinity** of \mathcal{L} for \mathcal{M} as $\mathcal{C}_{\mathcal{L},\mathcal{M}}^{(a)}$ (eq. 5). For a given number of ligands \mathcal{L} and binding sites \mathcal{M} , the affinity controls the fraction of bound pairs of molecules (adsorption isotherms) and an increased affinity leads to an increase of bound pairs. However, when many patterns $\mathcal{M}_1, \mathcal{M}_2, \dots$ compete for the same ligand, the affinity is not a good assessment of how exclusive is the binding of \mathcal{L} for a given \mathcal{M} . This is why one needs a **relative selectivity** parameter for comparing the respective behaviors of a ligand for a target (matching pattern \mathcal{M}) and for a decoy (mismatching pattern \mathcal{W}):

$$\mathcal{S}_r(\mathcal{L}, \mathcal{W}) = \frac{Z_{\mathcal{L}\cdot\mathcal{M}\text{bound}}}{Z_{\mathcal{L}\cdot\mathcal{W}\text{bound}}} \cdot \frac{Z_{\mathcal{W}\text{free}}}{Z_{\mathcal{M}\text{free}}}, \quad (10)$$

or equivalently $\mathcal{S}_r = \mathcal{C}_{\mathcal{L},\mathcal{M}}^a / \mathcal{C}_{\mathcal{L},\mathcal{W}}^a$. We will be also interested in the **absolute selectivity**, when comparing the affinity of the matching pattern with the affinity of a complete set of decoys:

$$\mathcal{S}_a(\mathcal{L}) = \frac{Z_{\mathcal{L}\cdot\mathcal{M}\text{bound}}}{Z_{\mathcal{M}\text{free}}} \cdot \frac{1}{\left[\sum_{\mathcal{W} \neq \mathcal{M}} \frac{Z_{\mathcal{L}\cdot\mathcal{W}\text{bound}}}{Z_{\mathcal{W}\text{free}}} \right]}, \quad (11)$$

if the ligand is given a choice between all the possible patterns, or

$$\mathcal{S}'_a(\mathcal{L}) = \inf_{\mathcal{W} \neq \mathcal{M}} \left\{ \frac{Z_{\mathcal{L}\cdot\mathcal{M}\text{bound}}}{Z_{\mathcal{M}\text{free}}} \cdot \frac{Z_{\mathcal{W}\text{free}}}{Z_{\mathcal{L}\cdot\mathcal{W}\text{bound}}} \right\}, \quad (12)$$

if only one decoy \mathcal{W} is present at a time. The inf operator of eq. (12) runs over all the possible patterns \mathcal{W} that are different from the matching pattern \mathcal{M} , and picks up the best competitor of \mathcal{M} , *i.e.* the one for which the affinity difference is the lowest. Eq. (11) is better suited for assessing the affinity of a ligand for its matching pattern, while all the other possible competitors $\mathcal{W} \neq \mathcal{M}$ are simultaneously present. This definition of the selectivity depends crucially on the set \mathcal{P} of allowed patterns \mathcal{W} . Changing this set \mathcal{P} results in changing the selectivity parameters $\mathcal{S}_{a,r}$. Using a subset \mathcal{P}' of \mathcal{P} naturally leads to higher selectivities. In practice, a large number of poor affinity decoys can eventually beat a good ligand-receptor pair [16].

3 A minimal model for flexible ligand and rigid receptor

We now introduce a model containing the basic components of the above discussion: matching, internal degrees of freedom, stiffness, information, and we search for phenomenon such as stiffness dependent affinity and matching-decoding.

The ligand \mathcal{L} is modeled as an articulated chain of n monomers. Each bead i is allowed to occupy only two positions labelled by a binary variable $s_i = \pm 1$ and the ligand can adopt 2^n distinct internal conformations. Ligand stiffness is enforced by means of next nearest neighbors couplings $J_{i,i+1} = \pm J$, in the spirit of the original spin-glass model by Edwards and Anderson [17, 18].

The signs of the couplings $\{J_{i,j}\}$ define the ground state shape (native shape) of \mathcal{L} , up to a trivial two-fold degeneracy, while the moduli $J = |J_{i,j}|$ describe the energetic cost associated to bending distortion of the ligand (strain). We assume that ligands have a well defined orientation, say from left to right, and we do not consider the possibility of left-right reversal. This can be justified considering that biopolymers (proteins, nucleic acids) always display such an orientation along the chain. Finally we also disregard the possibility of lateral shift between ligand and receptors, as occurring for instance in the hybridization of dna oligomers. This physically relevant situation increases significantly the combinatorics of the association and efficient algorithms have been designed to tackle these alignment problems [19]. In this work we purposely focus more on the thermodynamical stability of two molecules that are prepositioned in the right conformation, or which possess a unique, non-degenerated optimal relative conformation. The outcome of this schematic model is expected to be relevant on length scales of about 1 nm between consecutive “monomers”, large enough to invoke some coarse-graining of the underlying molecules, but small enough to preserve the importance of entropic, conformational degrees of freedom.

We now introduce a symbolic notation to describe the ground state of these flexible molecules. For that purpose, one must distinguish between *open*, free end molecules and *cyclic*, closed end molecules. Open ligands with n monomers have 2^n internal configurations. There are 2^{n-1} possible ground states, each one of them being doubly degenerated due to up-down symmetry. To fully describe the shape and ground state of a ligand, we denote by the letters **u** and **d** the position, respectively up or down, of the first monomer on the left. We then associate a **p** to each antiferromagnetic coupling constant $J > 0$, and a **m** to each ferromagnetic one $J < 0$. A symbol (**o**) is added at the end to signal an open chain. The ligand \mathcal{L} represented on the left of Figure 1 is thus ascribed to the symbol $\mathcal{L} = \mathbf{u/ppp(o)}$. The corresponding Ising configuration reads $s_1 = +1, s_2 = -1, s_3 = +1, s_4 = -1$, and the coupling constants are $J_{12} = J_{23} = J_{34} = J$.

Cyclic ligands with n monomers have spin s_1 and s_n coupled with a term $J_{n1}s_1s_n$. Cyclization is not really justified by the initial molecular association problem, it is

here just a convenient way to simplify calculations and get rid of boundary effects, giving to all monomers the same importance and simplifying the interpretation of results. Cyclic ligands of length n have the same number of configurations as open ligands, but it requires n coupling constants to fully determine their ground state. Cyclic ligands with an odd number of antiferromagnetic **p** couplings are “frustrated”, meaning that no ligand configuration can satisfy simultaneously all the constraints imposed by the $J_{i,j}$. The ground state conformation is then at least four-fold degenerated. Cyclic ligands with a even number of **p** have a well defined two-fold degenerated ground state. For instance, the unfrustrated cyclic ligand with the same shape as represented on the left of Figure 1 is coded as $\mathcal{L}' = \mathbf{u/pppp(c)}$, where the suffix (**c**) reminds of the cyclic character of the molecule. Ligand $\mathcal{L}'' = \mathbf{u/pppm(c)}$ is frustrated with no well defined ground shape. In this schematic approach, the use of open or cyclic ligands is essentially a matter of convenience, as they generate qualitatively similar results.

In the same way, the patterned receptor (binding site) is represented by a sequence of binary values $b_i, 1 \leq i \leq n$, each one taking a value ± 1 . When the ligand comes in contact with the receptor, it gains a negative stabilizing energy $-A$ whenever the monomer position s_i and the receptor value b_i match. We do not give a penalty to a mismatch situation $b_i \neq s_i$, but this could just be done by shifting negatively of the total configurational energy. The coupling constant A represents a short range interaction, possibly mimicking hydrogen bonding or hydrophobic patches. In both cases, the effective contact parameter A may depend on temperature. The resulting total “Hamiltonian” describing the ligand and the receptor in close contact is:

$$\mathcal{H}_r\{s_i\} = \sum_{i=1}^{n'} \left(J_{i,i+1} s_i s_{i+1} \right) - A \sum_{i=1}^n \delta_{s_i b_i}. \quad (13)$$

The sum runs until $n' = n - 1$ for open chains, and $n' = n$, with coupling $J_{n,n+1} = J_{n,1}$ for cyclic chains. As $\delta_{sb} = (1 + sb)/2$ for Ising variables, the Hamiltonian:

$$\mathcal{H}_r\{s_i\} = \sum_{i=1}^n \left(J_{i,i+1} s_i s_{i+1} \right) - \frac{A}{2} \sum_{i=1}^n (s_i b_i) - \frac{nA}{2}. \quad (14)$$

assumes the form of a random field Ising spin glass with both quench bond disorder J_{ij} and quenched random magnetic field $-Ab_i/2$. However, contrary to usual disordered systems studies, we do not perform here any average over the quenched random bonds, as these couplings contain the relevant information. The related partition function, expressed with the inverse Boltzmann factor β , is

$$Z_{\mathcal{L}, \mathcal{M} \text{ bound}} = \sum_{\{s_i = \pm 1\}} \exp \left(\frac{n\beta A}{2} + \sum_{i=1}^{n'} (-\beta J_{i,i+1} s_i s_{i+1}) + \frac{\beta A}{2} \sum_{i=1}^n (s_i b_i) \right). \quad (15)$$

Meanwhile, $Z_{\mathcal{M}\text{free}} = 1$ and $Z_{\mathcal{L},\text{free}}$ is a special instance of (15) with $A = 0$:

$$Z_{\mathcal{L}\text{free}} = \sum_{\{s_i = \pm 1\}} \exp\left(\sum_{i=1}^{n'} (-\beta J_{i,i+1} s_i s_{i+1})\right), \quad (16)$$

$$= 2^n [\cosh(\beta J)^n \pm \sinh(\beta J)^n],$$

result valid for cyclic chains, with a sign $+$ without bond frustration, and a sign $-$ otherwise.

Finally, from the binding free energy ΔF , defined as:

$$\Delta F = -k_B T \ln \left[\frac{Z_{\mathcal{L},\mathcal{M}\text{bound}}}{Z_{\mathcal{L}\text{free}} Z_{\mathcal{M}\text{free}}} \right], \quad (17)$$

one deduces the partial enthalpic ΔU and entropic $-T\Delta S_c$ contributions by numerically differentiating with respect to β .

$$\Delta U = \frac{\partial(\beta\Delta F)}{\partial\beta}; \quad (18)$$

$$-T\Delta S_c = \Delta F - \Delta U, \quad (19)$$

where it is assumed that A does not depend on temperature (enthalpic contribution).

To describe the shape of rigid receptors, it suffices, in principle, to enumerate the values b_i . However, anticipating the case of flexible receptors that will be considered in the coming section, we use for receptors the same convention as for ligands, *i.e.* a first letter **u** or **d**, followed by a list of couplings **p** and **m**. Receptors with matching ground state are called \mathcal{M} , \mathcal{W} being associated with those with mismatching ground states.

Let us illustrate the preceding section with $\mathcal{L}=\mathbf{u/pppp}(\mathbf{c})$, $\mathcal{M}=\mathbf{u/pppp}$ and $\mathcal{W}=\mathbf{u/pmpm}$. The coupling constants of \mathcal{L} are $\{J_{1,2} = J_{2,3} = J_{3,4} = J_{4,1} = J\}$, the matching motif corresponds to $b_1 = b_3 = 1$, $b_2 = b_4 = -1$ and the mismatching motif to $b_1 = b_4 = 1$, $b_2 = b_3 = -1$. The calculation of the partition functions by enumeration of the 16 configurations of \mathcal{L} , or with a transfer matrix method gives:

$$Z_{\mathcal{L}\text{free}} = 12 + 2e^{4\beta J} + 2e^{-4\beta J};$$

$$Z_{\mathcal{L}\mathcal{M}\text{bound}} = e^{4\beta J}(1 + e^{4\beta A}) + 4(e^{\beta A} + e^{2\beta A} + e^{3\beta A}) + 2e^{-4\beta J}e^{2\beta A}; \quad (20)$$

$$Z_{\mathcal{L}\mathcal{W}\text{bound}} = 2e^{4\beta J}e^{2\beta A} + 4e^{\beta A} + 2e^{2\beta A} + 4e^{3\beta A} + 2e^{2\beta A}e^{-4\beta J} + e^{4\beta A} + 1.$$

From now on, we assume that $k_B T$ sets the energy scale, and introduce the dimensionless coupling constants $a = \exp(\beta A/2)$, $j = \exp(\beta J)$. Affinity and selectivity are rational fractions of a and j .

$$\mathcal{C}_{\mathcal{L},\mathcal{M}}^a(a, j) = \frac{(1 + a^8)j^4 + 4(a^2 + a^4 + a^6) + 2a^4j^{-4}}{12 + 2j^4 + 2j^{-4}}, \quad (21)$$

and

$$\mathcal{S}_r(a, j) = \frac{(1 + a^8)j^4 + 4(a^2 + a^4 + a^6) + 2a^4j^{-4}}{2a^4j^4 + 4a^2 + 2a^4 + 4a^6 + 2a^4j^{-4} + 1 + a^8}. \quad (22)$$

We are interested in assessing the role of the stiffness parameter j . In Figure 2, we observe that the affinity of the ligand \mathcal{L} for the matching pattern \mathcal{M} increases monotonically with j . Figure 3 represents the variation with j of the thermodynamic potentials ΔF , ΔU and $-T\Delta S_c$.

At the opposite, the stiffness j reduces the affinity of \mathcal{L} for the mismatching pattern \mathcal{W} , as represented in Figure 4, with the thermodynamic functions shown in Figure 5. In addition, one notices that the special case $j = 1$ represents a soft ligand which can adapt to any pattern. Quite naturally, the selectivity between \mathcal{W} and \mathcal{M} is 1 for $j = 1$ and tend towards a finite value for $j \rightarrow \infty$ (Figure 6). The maximal selectivity depends on the short range contact parameter a and is reached as soon as $j \geq a$.

We conclude that stiffness is always favorable when the shape of a ligand and a receptor agree, but becomes unfavorable is a mismatch is present. When ligand and receptor shapes almost agree but not perfectly, there must be an optimal compromise between a very soft ligand $j = 1$, which precludes any selectivity at all, and a very hard ligand $j \gg 1$ which excessively penalizes the mismatches.

4 Flexible receptors

The next step is to consider flexible receptors \mathcal{M} : we expect then soft ligands to beat stiff ligands, as they will better fit the various configurations of \mathcal{M} . In our model, \mathcal{M} and \mathcal{L} play a dual role and it becomes possible to treat ligand and binding site (receptor) on the same footing, by inserting coupling constants K between the ‘‘spins’’ b_i . This situation arises when two molecules with similar weight and structure bind together (Figure 7).

$$\mathcal{H}_r\{s_i, b_i\} = \sum_{i=1}^{n'} \left(J_{i,i+1} s_i s_{i+1} \right) - A \sum_{i=1}^n \delta_{s_i b_i} + \sum_{i=1}^{n'} \left(K_{i,i+1} b_i b_{i+1} \right). \quad (23)$$

The problem can be naturally solved for cyclic ligands and receptors with 4×4 transfer matrices. When all the coupling constants have same absolute magnitude, we define $K_{i,i+1} = \eta_i |K|$, $k = \exp(\beta |K|)$, $J_{i,i+1} = \epsilon_i |J|$, $j = \exp(\beta |J|)$ where η_i and ϵ_i are ± 1 , to find:

$$Z_{\mathcal{L},\mathcal{M}\text{bound}} = a^n \text{Tr} \left(\prod_{i=1}^n T_{(a,j,k)}^{(\epsilon_i, \eta_i)} \right); \quad (24)$$

$$Z_{\mathcal{L}\text{free}} Z_{\mathcal{M}\text{free}} = 4^n [\cosh(\beta J)^n \pm \sinh(\beta J)^n] \cdot [\cosh(\beta K)^n \pm \sinh(\beta K)^n]; \quad (25)$$

(the sign \pm depending on the bond frustration along the chains) with noncommuting matrices defined as:

$$T_{(a,j,k)}^{(\epsilon,\eta)} = \begin{pmatrix} aj^\epsilon k^\eta & j^{-\epsilon} k^\eta & j^\epsilon k^{-\eta} & aj^{-\epsilon} k^{-\eta} \\ j^{-\epsilon} k^\eta & a^{-1} j^\epsilon k^\eta & a^{-1} j^{-\epsilon} k^{-\eta} & j^\epsilon k^{-\eta} \\ j^\epsilon k^{-\eta} & a^{-1} j^{-\epsilon} k^{-\eta} & a^{-1} j^\epsilon k^\eta & j^{-\epsilon} k^\eta \\ aj^{-\epsilon} k^{-\eta} & j^\epsilon k^{-\eta} & j^{-\epsilon} k^\eta & aj^\epsilon k^\eta \end{pmatrix}. \quad (26)$$

In computing the trace, one actually performs a summation over the 4^n internal configurations. Thermodynamic quantities ΔF , ΔS_c and ΔU , given by equations (17), (18) and (19), are then obtained by numerically differentiating the transfer matrix results. One notices that the transfer matrix is entirely built from dimensionless parameters a , j and k . The numerical differentiation of $\beta\Delta F$ with respect to β assumes that A , J and K do not depend on temperature, leading to $da/d\beta = \beta^{-1}a \ln(a)$, $dj/d\beta = \beta^{-1}j \ln(j)$ and $dk/d\beta = \beta^{-1}k \ln(k)$. As a result, the thermodynamic quantities derived from equations (17), (18) and (19) are automatically expressed in units $k_B T$. Non purely enthalpic contributions to the contact energy parameter A could also be included in this numerical scheme by using a different prescription for the derivative $da/d\beta$.

The external random field b_i which was quenched for rigid receptors is now annealed (the random bonds still quenched), and we checked that for large values of K (namely $k = \exp(\beta K) \geq 5$) the result for a flexible ligand-receptor pair tends to the predictions for the rigid receptor. One can easily convince oneself that there is no difference between a short rigid receptor and a short flexible receptor with doubly degenerated ground state (*i.e.* no frustration) for which the condition $k \gg j \gg 1$ holds. In this limit, $Z_{\mathcal{M},\text{free}} \simeq 2$, a factor which also appears in $Z_{\mathcal{L},\mathcal{M},\text{bound}}$, leaving $\mathcal{C}_{\mathcal{L},\mathcal{M}}^a$ unchanged. In practice, we regarded $k = 10$ as sufficient to reach the rigid situation. This corresponds to an energy gap of $3 k_B T$ between the receptor ground state and its first distorted state. Indeed, all the results regarding rigid receptors presented in this study were actually obtained by setting k to large values such as $k = 10$ and applying eq. (24).

To calculate the partition function of a flexible, open, ligand-receptor pair, one replaces the last matrix $T_{(a,j,k)}^{(\epsilon,\eta)}$ by a matrix $T_{(a,1,1)}$ representing the freely oscillating ends. Formula (24) becomes

$$Z_{\mathcal{L},\mathcal{M},\text{bound}} = a^n \text{Tr} \left(T_{(a,1,1)} \prod_{i=1}^{n-1} T_{(a,j,k)}^{(\epsilon_i,\eta_i)} \right); \quad (27)$$

The transfer matrix formalism can be modified if one wishes to pick-up a particular bond coupling $J_{i,i+1}$ and assign to it a value different from the usual J . In our numerical implementation of the transfer matrix product, we use a 5-letters alphabet $\{p, m, P, M, \cdot\}$ to describe a ligand pattern \mathcal{L} .

- Characters p and m are respectively used for $\epsilon = 1$ and $\epsilon = -1$.
- Character \cdot denotes a vanishing coupling constant $J = 0$ ($j = 1$).

- Characters P and M represent $\epsilon = 1$ and $\epsilon = -1$, but with a different (usually larger) magnitude of J or K .

Symbols P and M code for some localized hardening of ligand and receptors. Symbol \cdot loosely connects two adjacent and stiffer domains of \mathcal{L} . More complex scenarios can be considered, but all are subject to the same limitation, which is that these transfer matrices can deal only with nearest neighbor couplings.

5 Ligand stiffness and affinity

We now provide a list of examples illustrating various behaviors. All curves represent the affinity variations when the ligand stiffness is increased from $j = 1$ (soft ligand) till $j = 8$, *i.e.* a $2 k_B T$ activation barrier associated to local conformational change (spin reversal).

- **Uphill nonmonotonic affinity:**

Ligand $\mathcal{L} = \text{u/ppp.ppp(o)}$ vs $\mathcal{M} = \text{u/ppmmpm}$ (Figure 8)

The ligand \mathcal{L} is made of two loosely connected adjacent domains **ppp**. The resulting affinity is nonmonotonic, first increasing, then decreasing (Figure 9, a feature previously seen in Figure 4). This behavior emerges from a competition between the matching subdomain, favored by large values of the stiffness parameter j and the mismatching subdomain whose affinity decreases with j . In this particular case the mismatching domain forces the overall affinity to decrease below its starting point, a maximum being reached around $j \simeq 1.6$. Such a behavior illustrates the concept of optimal stiffness, where the association of a ligand with a (more) rigid receptor requires some tuning of its average rigidity.

- **Downhill nonmonotonic affinity:**

$\mathcal{L} = \text{u/ppppppp(o)}$ vs $\mathcal{W} = \text{u/ppmmpm}$ (Figure 10)

For $a = 2$ and $k = 10$ (rigid pattern), the affinity curve is not monotonic with j , first decreasing, then increasing (Figure 11). The affinity is minimal for a certain value $j \simeq 1.6$. This behavior is enhanced when a is increased and reduced when the receptor stiffness k is reduced, as seen in Figure 12. The interest of this situation is to be the exact opposite of the preceding situation, with a local affinity minimum for $j \simeq 1.6$.

- **Unbinding upon local hardening:**

Ligand $\mathcal{L} = \text{u/ppPpp(o)}$ vs $\mathcal{M} = \text{u/ppmmp}$ (Figure 13)

The receptor shows a slight mismatch located under a region in \mathcal{L} which is locally more rigid (stiffness $\bar{J} > J$) than the average coupling. Increasing \bar{J} while keeping J constant should hamper the capacity of \mathcal{L} to accommodate the mismatch, and lead to lower affinity. This is precisely what is seen in Figure 14. The effect is seen for open chains ($j = 1.5$, $j = 2$) and cyclic chains ($j = 2$). It is reduced if the average chain stiffness is larger ($j = 3$). If one admits that the stiff bond **P** is under control of an external agent or effector,

the issue is that the affinity of the ligand for its target decreases even though their shape are not altered. Figures 15 and 16 show respectively the energetic and entropic contributions to the changes in affinity associated with increasing the stiffness parameter \bar{j} . One can read from these data the associated relative entropy change $\Delta\Delta S = \Delta S(\bar{j}) - \Delta S(j)$. Ref [10] suggests that a positive $\Delta\Delta S$ can be associated to the decreased affinity of *lac*-repressor for dna in the presence of lactose. This change in $\Delta\Delta S$ arises from increasing one spring constant and decreasing another one, in an harmonic model of *lac*-repressor. In our case, because our model is not harmonic, changes in $\Delta\Delta U$ and $\Delta\Delta S$ cannot be separated and both contribute to changing the affinity. Note that if the hard bond P was located on top of a matching subdomain, the opposite behavior of the affinity with \bar{J} would occur. For instance the affinity of the pair $\mathbf{u/ppPpm(o)}$ - $\mathbf{u/ppppm}$ increases with large values of \bar{J} (not shown).

To sum up, by combining matching and mismatching subdomains and bonds of adjustable stiffness, it is possible to obtain a variety of nonmonotonic behaviors of a ligand affinity for its target. It turns out to be possible to control the mutual affinity by acting on the rigidity of selected bonds, mimicking possibly the influence of a cofactor (or effector) involved in some allosteric mechanism.

6 Selectivity and information decoding

Let us consider two persons A and B willing to communicate, and in possession of a number N of specific ligand-receptors pairs. A sends a ligand i to B , and B brings this (still unknown to him) ligand in contact with all the receptors available in his library. By using an analytical tool (fluorescence, quartz crystal microbalance, resonant surface plasmon absorption...) B determines the label i of the ligand he has received. By referring to a preestablished codebook, shared with A , B determines the content of the message. Information is conveyed to B by means of selective binding [20].

Information is coded in the shape of molecules, and especially biomolecules. When the biomolecule is in solution, this information about shape and chemical composition is made available to other molecules and a few of them will be able to selectively bind to it. Any selective adhesion process can be considered as information reading, or to be more precise, information decoding.

There are a number of issues raised by this medium of communication. One may be concerned by the reliability of the message transmission, directly connected to the absolute selectivity properties of the ligand-receptor pairs \mathcal{S}_a . One may also asks oneself whether there are physical bounds to the minimal binding energy or contact area necessary to ensure a transmission error rate lower than a predefined threshold value [21, 22].

Coding and decoding information is every day's concern for radio engineers, and many coding schemes have been developed in order to safely carry information around.

The simplified model discussed in the previous section establishes a convenient connection with the realm of digital information, as ligand and receptors are already described in terms of binary chunks of information.

6.1 Dependence in the number of mismatches

I now consider the selectivity of $\mathcal{L} = \mathbf{u/pppp(c)}$, in contact with altered configurations $\mathcal{W}_1 = \mathbf{u/pmmp}$ and $\mathcal{W}_2 = \mathbf{u/pmpm}$. Both altered patterns differ from the original one respectively by one and two values of the spin s_i (Hamming distances $d_H = 1$ and $d_H = 2$, cf Figure 17). However the Hamming distance relative to the stiffness pattern is $d'_H = 2$ for both \mathcal{W}_1 and \mathcal{W}_2 and is not directly related to the Hamming distance of configurations.

Results are shown in Figure 18. It seems that the selectivity bias is indeed lower for $d_H = 1$ than it is for $d_H = 2$. One expects two qualitatively different limits for the selectivity dependence in the number of mismatches. If the stiffness J is larger than the contact energy A , the selectivity is likely to correlate better with the Hamming distance d'_H between stiffness patterns: one can flip an entire interval of spins by changing only two characters in the stiffness pattern. In the opposite limit, the distance between configurations d_H should be dominant. Ref. [23] deals in details with related issues.

6.2 Selectivity of finite length symbols

We calculated the absolute selectivity (eq. 11) among the subset of all n -long ligand and receptor symbols, to determine the true amount of information that such a family of ligands may carry.

To be more precise, each ground state conformation \mathcal{L} among the 2^{n-1} possible ones (due to up-down degeneracy) was compared with its matching counterpart \mathcal{M} along with all the $2^{n-1} - 1$ other competitors \mathcal{W} , to define a shape-dependent gap of selectivity $\mathcal{S}_a(\mathcal{L})$, eq. (11). In this procedure, all bonds have the same stiffness j and the receptors are considered rigid, $k = 10$. This shape-dependent gap of selectivity was subsequently minimized with respect to all different possible \mathcal{L} , resulting in a quantity $\text{Gap}(a, j, n)$ characteristic of this family of ligands. In particular, $\text{Gap}(a, j, n)$ provides a lower bound for the occurrence of false positive if a ligand is put in contact with an equal number of all possible receptors. Using eq. (12) instead of eq. (11) leads to a different quantity $\text{Gap}'(a, j, n)$ related to the noise to signal ratio when transmitting a message using a library of compounds as suggested earlier in this section.

Finally, the lower bound $\text{Gap}(a, j, n)$ has to be optimized with respect to the internal parameters a and j , in order to assess, in a context independent manner, the intrinsic coding capacity of a family of ligands with given

length n , defining in this way $\text{GAP}(n)$. The resulting formulas are:

$$\text{Gap}(a, j, n) = \inf_{\text{ligands } \mathcal{L} \text{ of length } n} \left(\mathcal{S}_a(\mathcal{L}) \right); \quad (28)$$

$$\begin{aligned} \text{GAP}(n) &= \sup_{a, j} \text{Gap}(a, j, n) \quad (29) \\ &= \sup_{a, j} \left(\inf_{\text{ligands } \mathcal{L} \text{ of length } n} \left(\mathcal{S}_a(\mathcal{L}) \right) \right). \end{aligned}$$

The inf operator defines the selectivity bias of a matching receptor competing against a league of all other receptors. The sup operator maximizes Gap with respect to a and j .

In practice, cyclic chains were preferred to open chains, as they confer to all monomers the same importance. This optimization was performed by exhaustively scanning a rectangular grid of values $(a, j) \in [1, 9] \times [1, 9]$ with step 0.1, k being kept equal to 10. Our findings are rendered as a 2d plot of $\text{Gap}(a, j, n = 8)$ vs (a, j) (Figure 19), and shows that the gap increases with both a and j , but grows only marginally beyond $a, j \sim 2$. Thus, we took as representative the maximum obtained for $(a = 8.8, j = 8.8)$ for estimating $\text{GAP}(n)$. This arguably constitutes only a rough estimate of the $\sup_{a, j}$ operator of eq. (29). Similar results were observed for all the values of $n = 3, \dots, 8$ considered in this work. Values of $\ln[\text{GAP}(n)]$ are reported in Table 1. $\ln[\text{GAP}]$ decreases almost linearly with n (Table 1) as the number of decoys grows exponentially. Extrapolating to large n , $\text{GAP}(n)$ vanishes for $n \geq n^* \simeq 20$, length for which, in the presence of an equal number of all receptors, a ligand has more chance to bind a mismatching receptor than its own complementary one.

If one uses eq. (12) as an alternative definition of GAP, one observes a saturation of this quantity to a n independent value, close to $e^{4.33} \simeq 76$ (for $a = 8.8, j = 8.8, k = 10$, which are quite large values). This means that, irrespective of their length, any matching ligand receptor pair $\mathcal{L} - \mathcal{M}$ has an affinity larger by a factor 76 than any other mismatching pair $\mathcal{L} - \mathcal{W}$. Selectivity \mathcal{S}'_a is not sensitive to the growing number of decoys (or “complexity”) with n .

One learns from these results that if one wishes to preserve a minimal selectivity while increasing the ligand length n , one must necessarily select a subset of shapes as valid ligands and disregard the other possibilities. This is tantamount to introducing “redundancy” in the “coding scheme”. Note that the numerical value of Table 1 depends on the details of the a, j maximization and on the choice of k .

6.3 Sensitivity to stiffness profiles

The following step is to investigate the importance of stiffness patterns compared with shape patterns. Is it possible to encode information in the rigidity profile? This situation is motivated, for instance, by the bioinformatic study

of Sacquin-Mora *et al.* who investigated correlations between mechanical properties and binding location in proteins [24]. It would be indeed very interesting to determine whether self assembling pairs possess some kind of tactile sense and are sensitive to their respective local surface rigidity.

We consider four identically shaped ligands and receptors with patterns $\mathcal{L} = \text{u/PPppPP}(c)$ (ligand), u/PPppPP , u/PPPPpp , u/PpPpPp and u/ppPPpp (receptors), where p stands for a soft coupling and P for a stiff coupling (Figure 20).

The corresponding affinities are shown in Figure 21. The graph shows that the best affinity is observed when both patterns coincide (self) and the lowest when the stiffness pattern is opposite to the ligand (opposite). The mismatch u/PPPPpp is almost optimal and the intermediate case u/PpPpPp gives an intermediate value. The thermodynamic study shows that in both situations, the entropic contribution is dominated by the enthalpic contribution (Figures 23, 22 and 24). The stiffness patterns act on both enthalpic and entropic terms and the issue of the competition is not simple to predict. For instance, ligand $\mathcal{L} = \text{u/PpPpPp}(c)$ has a stronger affinity for $\mathcal{W} = \text{u/PPppPP}$ than for its self pattern \mathcal{M} (not shown).

If these results show that the affinity is sensitive to the stiffnesses, encoding information in stiffness profiles does not seem as straightforward as it is for shapes. Conveying information by means of selective binding, as sketched earlier in this section, would imply to design a quadruplet $\mathcal{L}_1, \mathcal{L}_2, \mathcal{M}_3, \mathcal{M}_4$ of ligands and receptors with identical shapes but distinct rigidity profiles, with affinities obeying:

$$\begin{aligned} \mathcal{C}_{\mathcal{L}_1, \mathcal{M}_1}^a &\sim \mathcal{C}_{\mathcal{L}_2, \mathcal{M}_2}^a; \\ \mathcal{C}_{\mathcal{L}_1, \mathcal{M}_2}^a &\sim \mathcal{C}_{\mathcal{L}_2, \mathcal{M}_1}^a; \\ \mathcal{C}_{\mathcal{L}_1, \mathcal{M}_1}^a, \mathcal{C}_{\mathcal{L}_2, \mathcal{M}_2}^a &\gg \mathcal{C}_{\mathcal{L}_1, \mathcal{M}_2}^a, \mathcal{C}_{\mathcal{L}_2, \mathcal{M}_1}^a. \end{aligned} \quad (30)$$

We could not come up with such a quadruplet. These quadruplets may not exist, or require longer lengths than the ones considered in this work (say $n \geq 8$). Stiffness profiles modulate the recognition process, but we were not able to prove that they could be substituted to shape profiles. We believe it is still an open issue to know for sure if stiffness profiles alone can bear some information.

7 Conclusion and Perspectives

It is clear that a ligand with too few degrees of freedom cannot achieve good selectivity. In the top of Figure 25, a fine receptor is in contact with a coarse ligand, which averages out the details of the receptor. If one changes one bit of the receptor, the binding properties of the ligand are only marginally altered, and the selectivity ratio stays close to 1.

At the opposite, a ligand with many monomers in contact with each element of the receptor, will have a greater tolerance to the fluctuations of a particular monomer (Figure 25, bottom). Binding is enhanced by the addition of

every monomer contribution. This case is a close analogous to the so-called “repetition code” in information theory. The repetition code consists in repeating many times every single bit of information to ensure the safe transmission of a code word (the message). It is a greedy procedure, as the length of the message is increased by the same factor. Here, a greater selectivity is achieved, at the expense of a greater complexity of the molecule \mathcal{L} which is thrice as long. As a rule, repetition is the easiest way one can come up with to amplify the trends observed in Figures 9 and 12. By glueing together copies of the same patterns, one automatically enhances the characteristics of the ligand-receptor repeated unit.

To summarize a comparison with the results presented in [11–13], we can say that we focussed mostly on interesting characteristic trends exhibited by a few selected pairs of ligand and receptors, while the authors of [11–13] favor global and averaged trends running over the whole set of possible patterns. Our definition of the Gap and GAP indicators differ from the free energy difference ΔF which serve as a criterion in their work. Our transfer matrix approach treats exactly the binding statistics of a given pair of ligand and receptor, without need of Monte-Carlo sampling, nor mean-field or large J approximations that are required in their 2d approach. Finally we believe that our model is the first one that makes it possible to investigate the role of local stiffness modulation, and the possibility of stiffness encoding of information.

The connection between error-correcting transmission codes and spin systems was recognized by N. Sourlas [25–27]. In particular, it was shown that the usual binary parity checks $b_1 \oplus b_2 \oplus \dots \oplus b_p$ which involves the sum of p binary digits modulo 2 was in fact equivalent to coupling p spins $s_1 s_2 \dots s_p$, with $s_i = \pm 1$, leading to a formal connection between information theory and p -spin glasses. Our model is currently restricted to nearest neighbors coupling, and cannot account for long range couplings. Information redundancy is thus limited to simple repetition codes. It would be interesting to investigate how a second layer of spins and couplings could be added in order to better enforce robustness with respect to single bit mismatches. One also notices that a 2d generalization of the ligand shape would indeed be equivalent to a genuine 2d Edwards-Anderson spin glass. Spin glasses are well known for their long-lived or metastable states [18,28]. Each one of these states can be put in correspondence with a matching random-field representing a different receptor.

Another interesting connection between spin systems and pattern recognition, is the *Superparamagnetic clustering of data* [29,30]. Wiseman, Blatt and Domanyi showed that it was possible to train a two dimensional array of Potts spins in order to recognize picture features and patterns (2d inhomogeneous distributions of points). This work could provide hints on how to train a 2d elastic network for shape and stiffness recognition.

The nonmonotonic behaviors of the affinity, or the decrease of affinity upon local stiffening of the chain are still modest, showing only a cut by half in the case illustrated

in Figure (14). One may be interesting in finding stronger effects by hardening more than a single bond.

The schematic model introduced and studied here is intended to guide us towards more realistic examples, such as simple molecules that could be designed and investigated with the help of *coarse grained* or *all atom* numerical models. This, we believe, should be the next step to endeavor.

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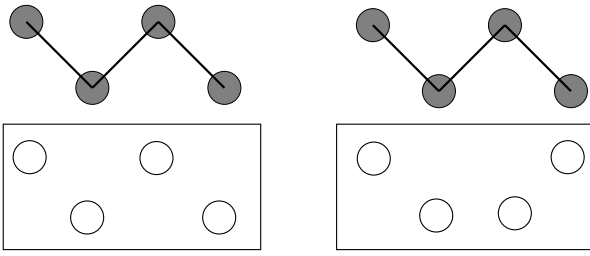


Fig. 1. Picture of the ground state of a ligand molecule $\mathcal{L} = u/ppp(o)$ and a matching receptor $\mathcal{M} = u/ppp$. With 4 monomers, the flexible ligand explores $2^4 = 16$ configuration states, while the rigid receptor does not change its conformation. On the right, a mismatching pattern $\mathcal{W} = u/pmp$ is shown.

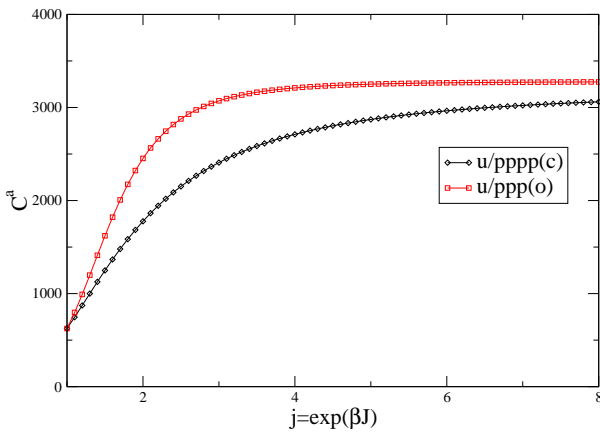


Fig. 2. Affinity \mathcal{C}^a of open $\mathcal{L} = u/ppp(o)$ and cyclic $\mathcal{L}' = u/pppp(c)$ with their rigid matching receptor \mathcal{M} , (Figure 1 on the left) as a function of the ligand stiffness parameter j , with $a = 3$. Here stiffness is shown to enhance the affinity of the pair. A ligand whose native state matches the binding site of a receptor is said to be *pre-organized* for matching.

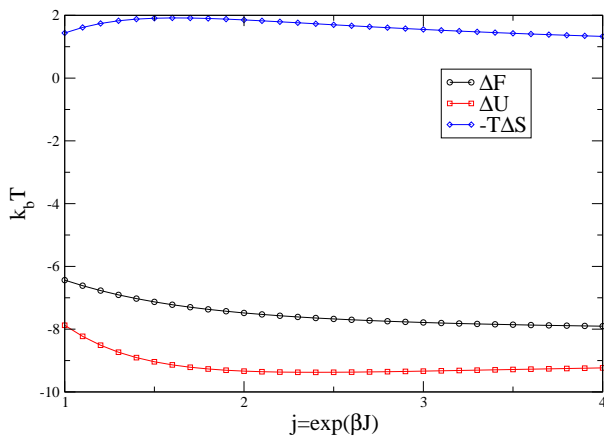


Fig. 3. Thermodynamics of $u/ppp(o)$ on its matching receptor, $a = 3$, expressed in units $\beta^{-1} = kT$

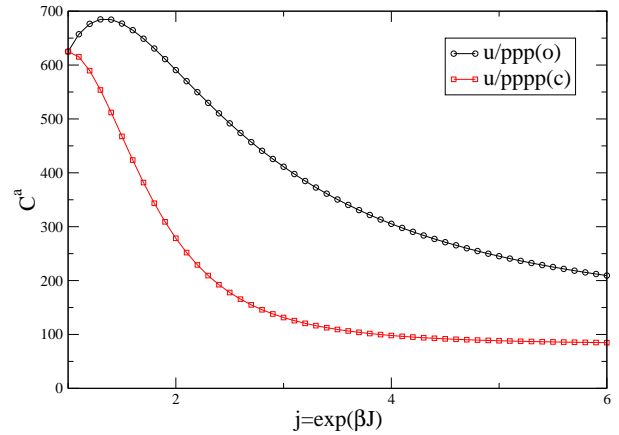


Fig. 4. Affinity \mathcal{C}^a of ligands $\mathcal{L} = u/ppp(o)$ and $\mathcal{L}' = u/pppp(c)$ with a mismatching rigid receptor (decoy $\mathcal{W} = u/pmp$, Figure 1 on the right). The stiffness j decreases the affinity of the cyclic pair while the affinity of the open chain decreases shortly after a maximum. Here $a = 3$.

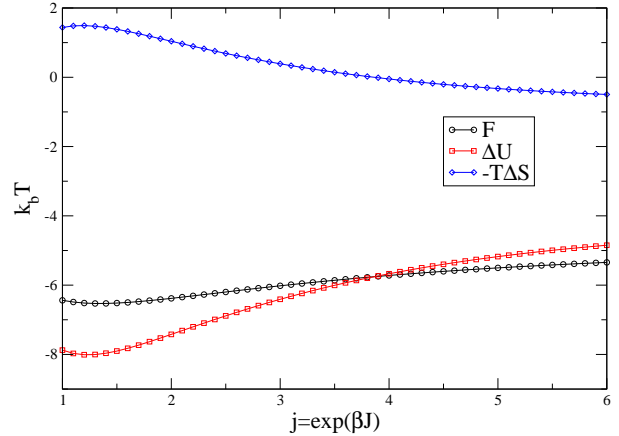


Fig. 5. Thermodynamics of $\mathcal{L} = u/ppp(o)$ on receptor $\mathcal{W} = u/pmp$, $a = 3$, expressed in units $\beta^{-1} = k_B T$.

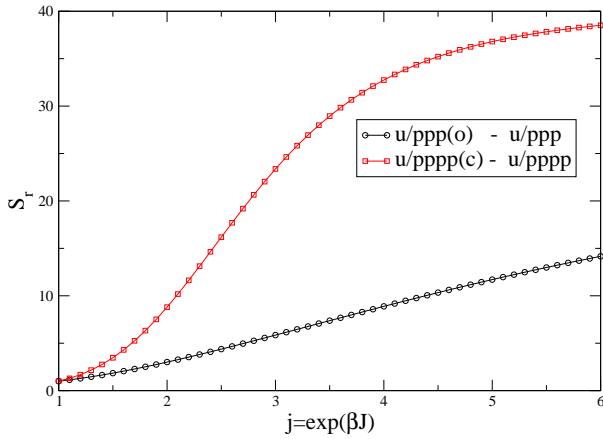


Fig. 6. Selectivity S_r between ligand $\mathcal{L} = u/ppp(o)$, $\mathcal{L}' = u/pppp(c)$, their matching rigid receptor $\mathcal{M} = u/ppp$ and a mismatching receptor $\mathcal{W} = u/pmp$, as a function of the ligand stiffness j (see eq. 10). S_r is directly related to the probability of the ligand to bind the decoy instead of the matching pattern. As expected $S_r = 1$ when $j = 1$ because a completely soft ligand binds equally well any receptor (non specific binding). Here $a = 3$.

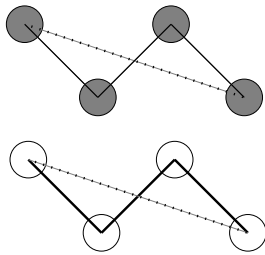


Fig. 7. Ground state shape of flexible cyclic ligand $\mathcal{L} = u/pppp(c)$ and flexible receptor $\mathcal{M} = u/pppp$. The 4 monomers ligand and receptor are treated on the same footing, and the partition sum encompasses $4^4 = 256$ configuration states, which is done by tracing the fourth power of a transfer matrix.

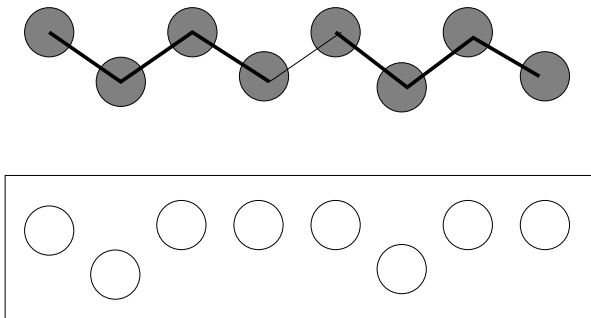


Fig. 8. Ground state shape of ligand $\mathcal{L} = u/ppp.ppp(o)$ and motif $\mathcal{M} = u/ppmmpm$, involved in Figure (9). The dot stands for a very weak coupling constant between monomers 4 and 5.

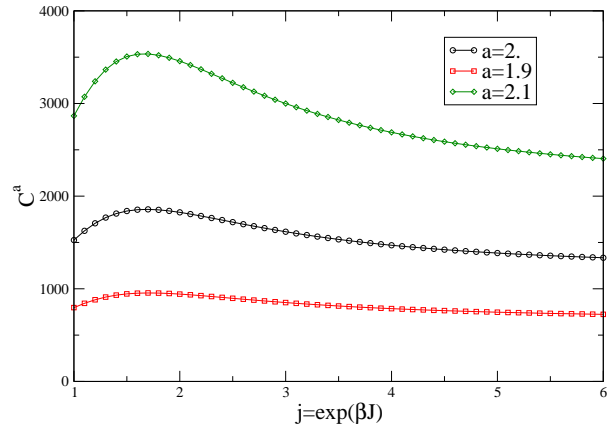


Fig. 9. Nonmonotonic behavior of the affinity \mathcal{C}^a vs j for $\mathcal{L} = u/ppp.ppp(o)$, $\mathcal{M} = u/ppmmpm$, $k = 10$. The effect is more pronounced for larger values of a .

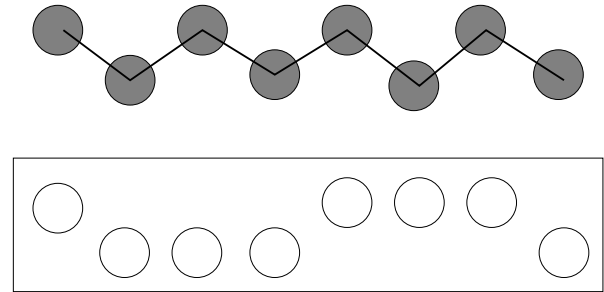


Fig. 10. Ground state shape of flexible ligand $\mathcal{L} = u/pppppp(o)$, and rigid receptor $\mathcal{W} = u/pmmpmmp$ involved in Figure (11).

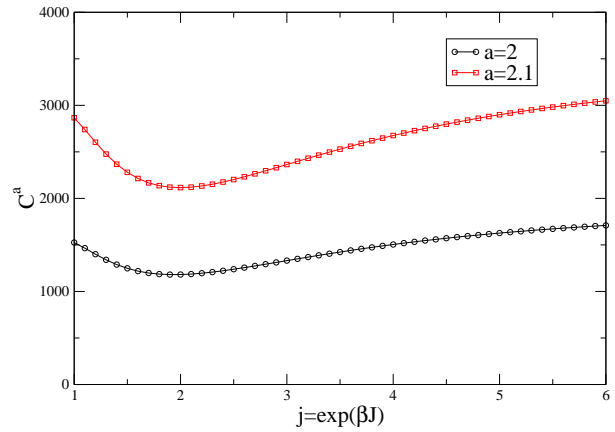


Fig. 11. Nonmonotonic downhill behavior of the affinity \mathcal{C}^a vs j for $\mathcal{L} = u/pppppp(o)$, $\mathcal{M} = pmmpmmp$, $k = 10$. The effect is more pronounced when a increases.

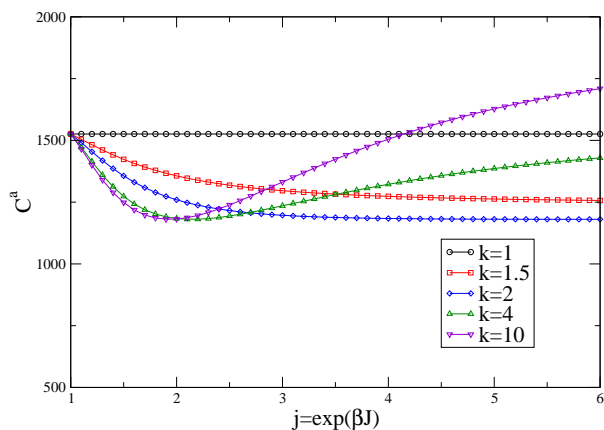


Fig. 12. Nonmonotonic behavior of the affinity \mathcal{C}^a vs j for $\mathcal{L} = \text{u/ppppppp}(\circ)$, $\mathcal{M} = \text{u/pmmpmmp}$, $a = 2$. The effect disappears when the flexibility k of the receptor decreases and the limit case $k = 1$ corresponds to a very soft, patternless receptor.

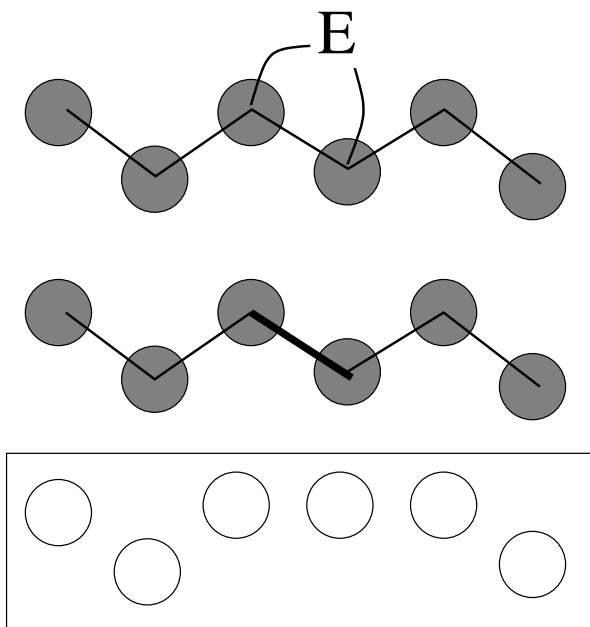


Fig. 13. Ground state shape of cyclic ligand $\mathcal{L} = \text{u/ppPppp}(\circ)$ and motif $\mathcal{M} = \text{u/ppmmp}$ involved in Figure 14. The ligand possesses a hard bond (thick line) between monomers 3 and 4. This hard bond can be understood as being caused by the presence of an effector E that bridges the two neighboring beads 3 and 4.

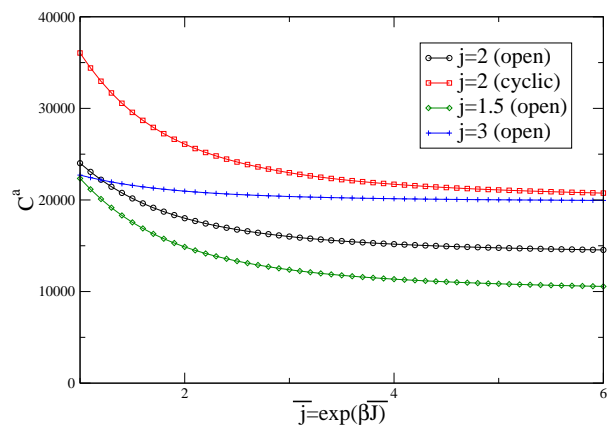


Fig. 14. Affinity \mathcal{C}^a as a function of the stiffness $\exp(\beta \bar{J})$ of the hard link, with $j = \exp(\beta J) = 2$ and $a = \exp(\beta A/2) = 3$. Because the stiff bond of the ligand lies on a mismatching region, its hardening leads to a decrease in the affinity. Assuming that an effector molecule is the cause of this bond stiffening, as sketched in Figure 13, one is left with a situation that reminds the proposed mechanism of Hawkins and McLeish. At the opposite, when the stiff bond lies on a matching region, its hardening leads to an increase of the affinity (not shown).

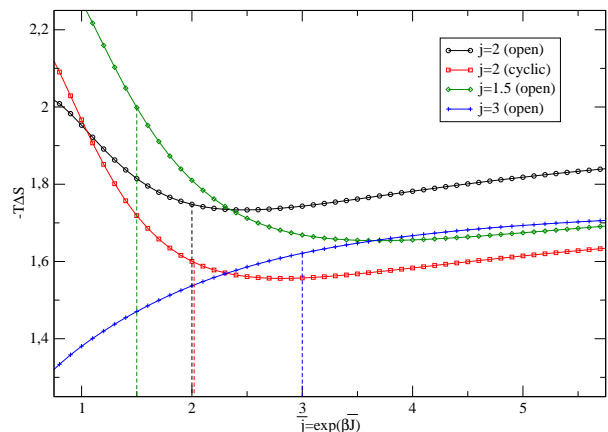


Fig. 15. Configurational entropy change $-T \Delta S_c$ upon binding, when the stiffness of the bond linking bead 3 and 4 is increased (Figures 13 and 14). The vertical dashed lines indicate the points where all bond stiffnesses are identical ($\bar{j} = j$). One can infer from these curves the relative variation of configurational entropies $\Delta \Delta S$ caused by a change in \bar{j} . For instance $\Delta \Delta S$ is positive (binding is favored) for $\bar{j} \geq \bar{j} = 1.5$. The trend is reversed for $\bar{j} \geq \bar{j} = 3$., and unsettled for $\bar{j} \geq \bar{j} = 2$.

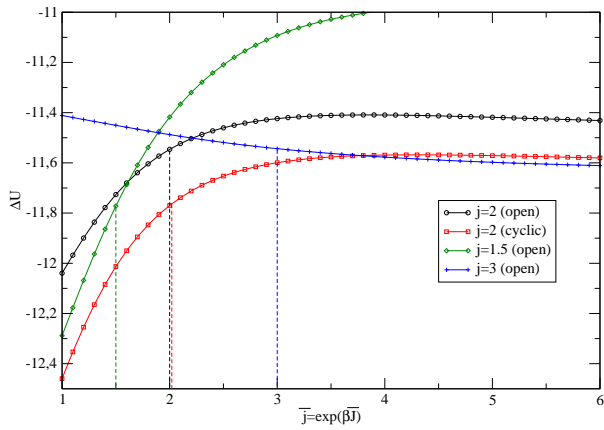


Fig. 16. Energy (enthalpy) change ΔU upon binding, when the stiffness of the bond linking bead 3 and 4 is increased (Figs 13 and 14). The vertical dashed lines indicate the points where all bond stiffnesses are identical ($\bar{j} = j$). The relative energy change $\Delta\Delta U$ is positive (binding is unfavored) for $j = 1.5$ and $j = 2$, but slightly negative for $j = 3$.

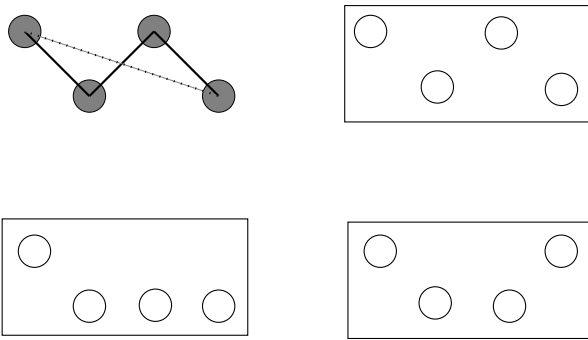


Fig. 17. Ligand $u/pppp(c)$ (top left) with a matching receptor $u/pppp$ (top right), mismatching receptors $u/pmmp$ (bottom left) and $u/pmmp$ (bottom right). The Hamming distances in terms of configuration are respectively $d_H = 0, 1$ and 2 , while in terms of stiffness one has $d'_H = 0$ and $d'_H = 2$.

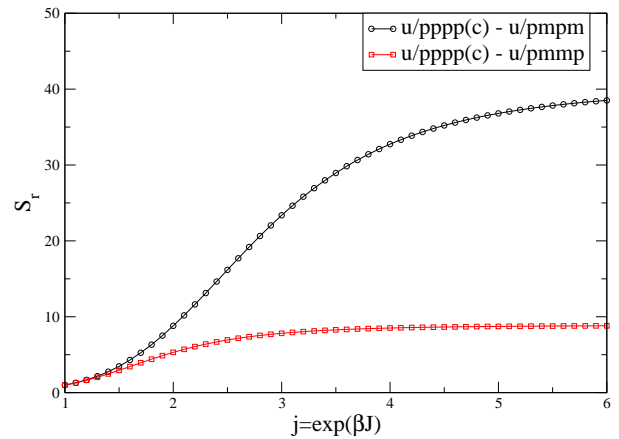


Fig. 18. Selectivity S_r for Hamming distance $d_H = 1$ (straight lines) and $d_H = 2$ (circles). The selectivity of the pair $u/pppp(c)$ - $u/pmmp$ is higher than the one of $u/pppp(c)$ - $u/pmmp$, which means that $u/pppp(c)$ binds $u/pmmp$ ($d_H = 1$) better than $u/pmmp$ ($d_H = 2$). Other parameters are $a = \exp(\beta A/2) = 3$ and $k = \exp(\beta K) = 10$.

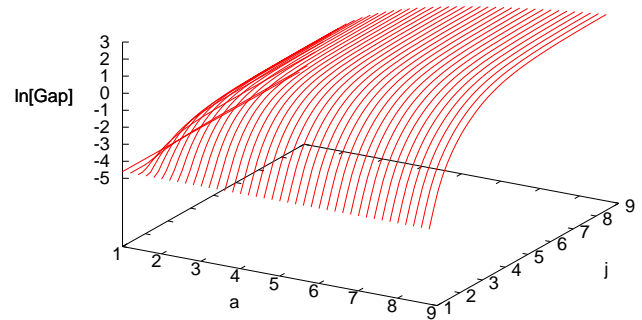


Fig. 19. Three dimensional graph of the relative selectivity $\ln[\text{Gap}(a, j, 8)]$ as a function of a and j , for patterns with length 8. Selectivity increases slowly with a and j . Receptors are rigid, $k = 10$.

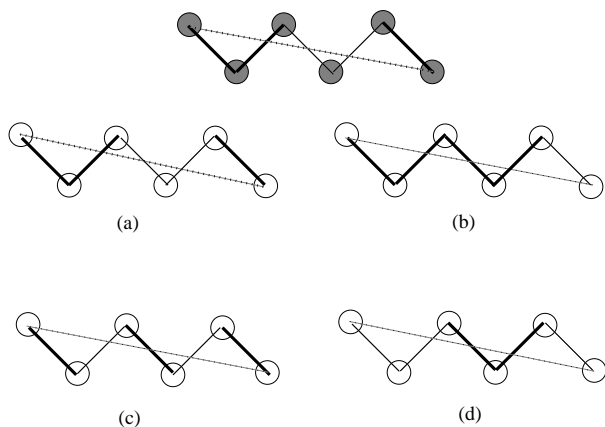


Fig. 20. A ligand and four receptors with same shape but different rigidity patterns are represented. The ligand is $\mathcal{L} = \text{u/PPppPP(c)}$, made of two rigid bonds, two soft bonds and then two rigid bonds (top). The receptors are (a) middle left u/PPppPP , (b) middle right u/PPPPpp , (c) bottom left u/PpPpPp , (d) bottom right u/ppPPpp .

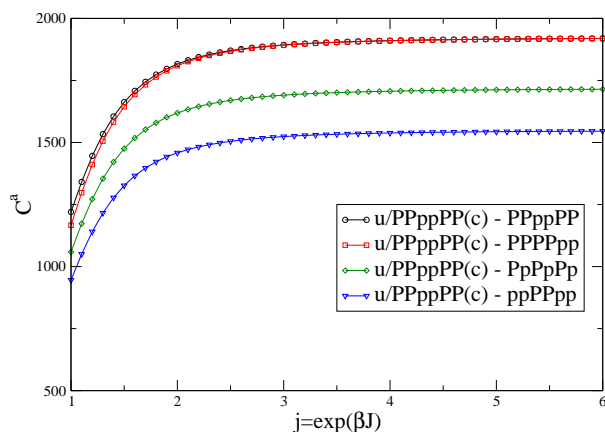


Fig. 21. Affinities C^a for the four pairs introduced in Figure 20 as a function of j (stiffness of the soft bonds of the ligand, symbol \mathbf{p}, \mathbf{m}), see text for details. Parameters are $a = 2$, $k = 2$, $\bar{k} = 10$ (receptor hard bonds with symbol \mathbf{P}, \mathbf{M}), $\bar{j} = 10$ (ligand hard bonds with symbol \mathbf{P}, \mathbf{M}).

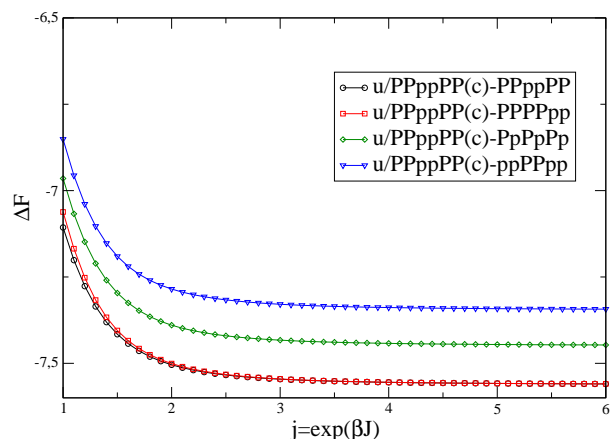


Fig. 22. Free energy differences in the case of Figure 20 and Figure 21 result from a competition between energy (enthalpy) and entropy, where the energy term is larger by a factor 2 compared with the entropic one.

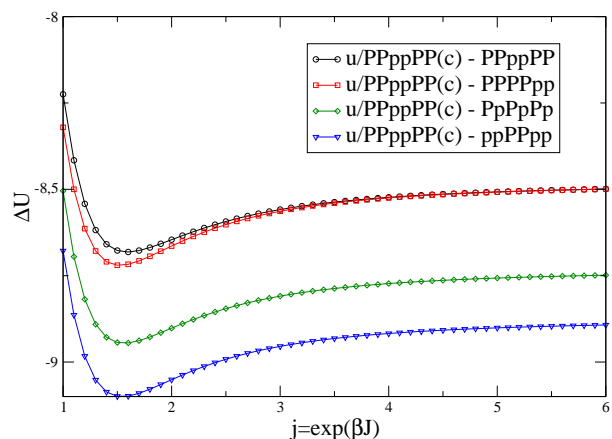


Fig. 23. Energy (enthalpy) differences in the case of Figure 20 and Figure 21 dominates the thermodynamics of binding.

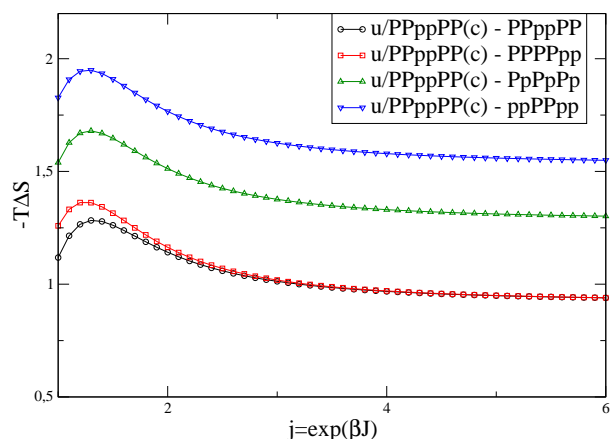


Fig. 24. Differences in entropy $-T \Delta S_c$. The entropy loss is minimal for identical stiffness profile and maximal for opposite stiffness profile.

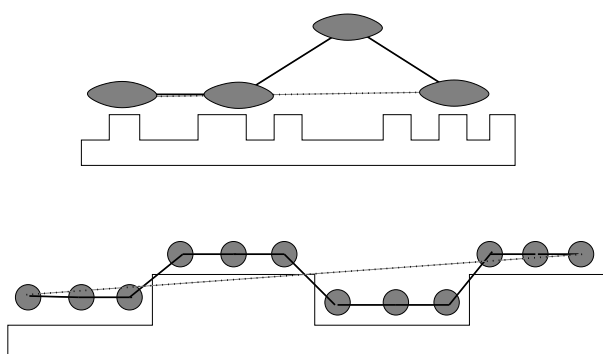


Fig. 25. A coarse molecule and a fine receptor (top), a fine molecule and a coarse receptor (bottom).

Length n	$\ln(\text{GAP})$
2	3.65
3	3.22
4	2.91
5	2.67
6	2.47
7	2.30
8	2.15

Table 1. Table of selectivities for patterns with increasing sizes. See text for details.