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# Identifying Abstract and Concrete Words in French to Better Address Reading Difficulties

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## Abstract

Literature in psycholinguistics and neurosciences has showed that abstract and concrete concepts are perceived differently by our brain, and that the abstractness of a word can cause difficulties in reading. In order to integrate this parameter into an automatic text simplification (ATS) system for French readers, an annotated list with 7,898 abstract and concrete nouns has been semi-automatically developed. Our aim was to obtain abstract and concrete nouns from an initial manually annotated short list by using two distributional approaches: nearest neighbors and syntactic co-occurrences. The results of this experience have enabled to shed light on the different behaviors of concrete and abstract nouns in context. Besides, the final list, a resource *per se* in French available on demand, provides a valuable contribution since annotated resources based on cognitive variables such as concreteness or abstractness are scarce and very difficult to obtain. In future work, the list will be enlarged and integrated into an existing lexicon with ranked synonyms for the identification of complex words in text simplification applications.

**Keywords:** text simplification, abstract and concrete nouns, semantic annotation, lexicon.

## 1. Introduction

The existence of differences in the brain for processing abstract and concrete words has been proven by researchers in the field of cognitive sciences. The basis for these studies is a dual-coding theory, described by Paivio (1965; 1991) consisting of two separate cognitive subsystems – two ways, verbal and non-verbal, of decoding the information. Their activation would depend on the degree of abstractness of the word. If concrete words use these two systems equally because they have an image as a support in the memory of the speaker, abstract words can only be decoded by a verbal system. Later this theory has also been proved by event-related potential (ERP) and functional magnetic resonance imaging (fMRI) tests (Just et al., 2004), which showed the detailed distinction between different brain zones activation during the processing of abstract and concrete words.

Relying on this theory, one could presuppose that concrete words have an advantage over abstract words in the task of word recall, since they benefit of two ways of decoding. The hypothesis has been confirmed by Kroll & Merves (1986) and James (1975) who refer to the ease with which a word evokes a mental image, as to the semantic factor which facilitates the recognition of words in the lexical decision task. And also by Shallice (1988) and Schwanenflugel (1991), who state that highly imaginable words have a richer or more easy accessible semantic representation.

Recently, Crutch and Warrington (2005) proposes that representations of concrete words are organized in a hierarchical structure (categorical organization), while abstract words are mainly represented by semantic associations. This theory maintains that concrete words share more representations with other similar words (for

example, cow - sheep) than with other associated words (for example, cow - barn), while abstract words share more representations with other associated words (for example, theft - punishment) than with other similar words (for example, theft - crime). This can be reviewed from the point of view of another explanation for the concreteness effect in the framework of context availability theory (Schwanenflugel et al., 1988; Schwanenflugel & Shoben, 1983; Schwanenflugel & Stowe, 1989), which argues that concrete words are strongly associated with some contexts, while abstract words are weakly associated with many contexts, and the representations of abstract words have less conceptual overlap because these words appear in more disparate contexts, although they are semantically related (Schwanenflugel & Shoben, 1983).

In the 60s – 80s of the twentieth century, the question of the influence of the word's imageability on its perception and its impact in the complexity of texts was raised, particularly in people with deep dyslexia, and later on in normal readers. Paivio (1968) and Jones (1985) conducted a series of experiments separately to determine the level of word iconicity and the factors influencing the perception of the word as an abstract word in English (Canadian English in the first case and British English in the second). Jones (1985) conducted a study in non-dyslexic subjects with the task to annotate a list of words with high and low level of imageability, and to determine on a scale from 1 to 7 the ease of putting these words into simple factual statements. The results coincided with the researcher's hypotheses (except for a few words): concepts such as 'dog' are easy to put into simple factual statements (ex., the dog has four legs, the dog is a pet, the dog barks) than more abstract words such as 'idea'.

In this paper, we aim at identifying abstract and concrete words in French to develop a lexical database for French by bootstrapping from an initial manually annotated short

list. In the following sections, we first address the issue of characterizing abstract and concrete words (section 2). In section 3, we describe the methodology to annotate French nouns bootstrapped from an initial short list by using two distributional approaches, nearest neighbors and syntactic co-occurrences. In section 4 we present the experimental setup, the initial word list and the results of the first two stages for extending the database. We finally conclude with an analysis of the results obtained after a comparison with human judgements and a discussion on the possible usages of the resource, namely its integration into an automatic text simplification (ATS) system to measure the impact of the abstract/concrete notion in the identification of complex words during reading.

## 2. Identifying Abstract and Concrete words

### 2.1 On the notions of Abstractness and Concreteness

Concreteness is the quality or state of being concrete, i.e. relating to an actual, specific thing or instance. The ‘concreteness effect’ refers “to the observation that concrete nouns are processed faster and more accurately than abstract nouns in a variety of cognitive tasks” (Jessen et al., 2000). Various theories explaining this effect in normal readers and people with reading disabilities are proposed in the literature. Plaut and Shallice (1993), in their connectionist model, consider an advantage for reading concrete words, due to the facility of their characterization. This is confirmed by a recent study that has showed an impact of word imageability and word regularity in word reading accuracy and word learning efficiency (Steacy & Compton, 2019). There is an evidence that imageability, the feature that describes the degree of ease with which a word provokes the appearance of a mental image in the reader’s mind (Paivio et al., 1968), significantly impacts word reading accuracy and rate of word learning.

Categorizing words into concrete and abstract remains a difficult task. According to Tellier and colleagues (2018), concrete words are associated to great iconicity, particularly in terms of mental representation, while abstract words are rather verbally encoded (Paivio, 1986). Concrete words are more associated with contextual information and sensorimotor experiences than abstract words, insofar as, as pointed out, among others, concrete words are linked to high imageability and abstract words to low imageability (Paivio, 1986 and Palmer et al., 2013). Following Gorman (1961), the notion of ‘concrete noun’ refers to objects, materials, sources of *relatively direct* sensation, while the notion of ‘abstract noun’ refers to objects, materials, and sources of *relatively indirect* sensation, with social or introspective information (Danguécan & Buchanan, 2016), see Table 1. However, Gorman (1961) claims that both abstract and concrete words can be general (name a group or a category) or specific (name a specific idea or an object).

A clear division of words into an abstract or a concrete category, however, remains quite subjective due to the fact that, firstly, each person has a different language experience and background, and secondly, in the

vocabulary of any language, there are many polysemic words that often have meanings related to different categories on the concreteness scale.

Abstract words		Concrete words	
Processes, states and periods	lockdown, hope, month	Spatially perceptible	table, tree
Measures and qualities	degree, kindness	Physically perceptible by one of the five senses	music, rainbow, bitterness
Phenomena and events	advice, party	All living beings	women, cat
Human features	liar, genius	Mythological creatures	troll, dragon

Table 1. Abstract/Concrete typology (Danguécan & Buchanan, 2016; Dove, 2016)

Even though the binary nature of such a division may seem an obstacle to the accuracy of the classification, in our work we adhere to such a categorization. We believe that if previous studies were able to prove the difference in the perception of abstract and concrete words by the human brain, the line between abstractness and concreteness exists in the lexicon and can be reflected in specific inherent features in the vocabulary.

With the advent of automatic tools for natural language processing (NLP), an increasing interest has been shown in the possibility of automatic disambiguation of semantic features. Automatic annotation of abstract/concrete words remains nevertheless an area that is not sufficiently covered in research papers. Abstractness and concreteness being semantic properties, with no link with formal features (length, frequency, etc.), this increases the difficulty to obtain accurate annotations from raw corpora. The existing databases reported in the literature are usually based on the results of human annotations (Brysbaert et al., 2014). Databases for French are rare and contain a small amount of information (Bonin et al., 2003; Ferrand, 2001; Ferrand & Alario, 1998). They have mainly been developed for psycholinguistic experiments.

### 2.2 State-of-the-Art Methods to Annotate abstract and concrete words

Different attempts to build annotated lists of abstract and concrete words are reported on the literature. Rabinovich and colleagues (2018) use a weakly supervised approach to infer the abstraction property of words and expressions in the complete absence of labeled data. They exploit morphological cues as suffixes and prefixes and the contextual surroundings of a word as it appears in text. Their results show that the proposed heuristics are powerful enough to obtain a high correlation with human labels. The results also demonstrate that a minimum morphological information and a text corpus are enough to provide predictions (the authors used a set of “abstractness indicators” in English, i.e. suffixes like *-ness*, *-ence*, *-ety*, *-ship* etc.).

Other research (Marslen-Wilson et al., 2013) shows different degrees of concreteness for derived word-forms on the mental representation in English. Words with an opaque structure, i.e. words with a meaning that is not clearly linked to their stem in synchronic linguistics (for instance, “department”) can be more difficult to categorize than words that can be easily decomposed into a stem with a transparent meaning and a suffix (“friendship”).

With the rising of word embedding techniques the direction of the research has slightly changed, since this method allows to automatically extend distributional networks using the semantic proximity information presented as vectors. Studies involving the use of the word embedding algorithms for predicting the concreteness of words in one language and between languages have been proposed by Ljubešić and colleagues (2018). The question of the stability in word embeddings, depending on the assignment to the category of concrete or abstract, has also been studied by Pierrejean & Tanguy (2019). The results of this study have shown better stability of concrete words compared to abstract. Finally, Abnar and colleagues (2018) have carried experiments using multiple algorithms to compare their performance to the results of brain activity with the goal to find a better solution for the future word-sense disambiguation in abstract and concrete nouns. With word embeddings, as abstract concepts are mostly associated with abstract concepts, they appear in similar contexts and overall behave alike in a semantic space. Concrete concepts are also strongly associated with concrete concepts and appear in similar contexts.

There is no doubt that word embeddings are very powerful methods in NLP. However, as well as many other machine learning mechanisms, they often represent a ‘black box’ for the researcher: what is happening inside the algorithm operation remains vague and limits the interpretability of the results (Chen et al., 2018).

### 3. Experimental setup

#### 3.1 Objectives

In our study we are interested not only in what is happening after the application of a NLP algorithm, but also in what is happening inside the ‘black box’, i.e. how close is one or another algorithm of word embedding to a human judgement, and for which category, Abstract or Concrete, we can obtain better results. Our aim is to identify whether it is possible to bootstrap from a manually annotated list of words in order to enrich an existing database where words have been ranked according to their reading difficulty (Billami et al., 2018). We also aim at finding out whether this bootstrapping works better for abstract or for concrete nouns. Our hypothesis is that abstract nouns are semantically linked to other abstract nouns and concrete nouns are semantically linked to concrete nouns. We avoid using the term “synonyms” because this term has a restricted connotation. The distributional methods we use in our study, in addition to synonyms, may include other lexical relations such as analogies, antonyms and word associations.

#### 3.2 Methodology

In order to enrich our initial short list of abstract and concrete nouns, we used two different types of relations: nearest neighbors (*voisins distributionnels*) and syntactic co-occurrences (*co-occurents syntaxiques*) extracted from the French lexical database Le Voisins De Le Monde<sup>3</sup>. Nearest neighbors are words that share the same contexts, while syntactic co-occurrences are words that frequently appear next to a target word (van der Plas, 2009). For instance, ‘plante’ (plant) and ‘fleur’ (flower) are nearest neighbors of the concrete word ‘arbre’ (tree), while ‘branche’ (branch) and ‘ombre’ (shadow) are syntactic co-occurents. ‘Inquiétude’ (worry) and ‘peur’ (fear) are nearest neighbors of the abstract word ‘crainte’ (dread), while ‘dissipation’ (dissipation) and ‘reflet’ (reflect) are found as syntactic co-occurents.

We decided to base our research on these two methods because they show two distinct relations of semantical bonds in context. We made the hypothesis that this would be crucial for automatically identifying and distinguishing abstract and concrete words in context. In our study we investigated which of these two approaches was closer to human judgements: how many units from the output subset of nearest neighbors and syntactic co-occurents obtained would better correspond to the human evaluation results.

We were also interested in differences in accuracy of prediction between abstract and concrete words and in the differences in the size of semantic networks of abstract and concrete words, if there were any. According to the theory of Schwanenflugel & Shoben (1983), abstract words appear in more varied contexts while concrete words appear in less contexts. Crutch & Warrington (2005) suggest that concrete words are organized following a semantic similarity principle, whereas abstract words are organized by their association with other words. In this work, we wanted to study if a quantitative prevalence and/or a greater homogeneity could be found in the results for abstract or concrete words during the extension of the primary list and/or as a result of the human evaluation.

#### 3.3 Data

To automatically annotate words by using nearest neighbors and syntactic co-occurents, we first created an initial short list of words from two studies for French (Ferrand, 2001; Ferrand & Alario, 1998) which contain 260 and 366 nouns respectively, with annotations according to abstractness and concreteness scales (see Appendix A).

To create our initial list, we chose 19 abstract nouns (Ferrand, 2001) and 42 concrete nouns (Ferrand and Alario, 1998) with a high frequency score ( $\geq 40$ ) according to the lexical database for French Lexique 3<sup>1</sup>. Abstract nouns are monosemic according the lexical resource with graded synonyms ReSyf<sup>2</sup> (Billami et al., 2018). Nouns from the study of Ferrand and Alario (1998) annotated with a high concrete value and with a high frequency indicator<sup>1</sup> were often polysemic<sup>2</sup>. We decided to avoid them and to keep only monosemic concrete words (without abstract meanings, e.g. bread, hand, house, journal, etc.). Unlike concrete words, abstract words were mostly monosemic

(they did not have other concrete meanings, e.g. joy, friendship, hatred, happiness, etc.).

The next step was to manually extract syntactic co-occurrences and nearest neighbors from the distributional database Les Voisins De le Monde<sup>3</sup> available online: 50 lexical units for each noun for the further bootstrapping process. The initial experimental dataset was reduced to only 50 nearest neighbors as we identified that after 50 first neighbors the distance from the target word according to the values given by the database became more important. In short, the relations became too distanced (according to the distance scores provided by Les Voisins De Le Monde). After these first two steps, we had a first list of 2,503 words from which we removed repetitions, non-nouns and words with a different part-of-speech of the target word. Finally, we obtained a full experimental list consisting of 369 units (180 concrete ad 189 abstract nouns) (see Table 2).

Category	Abstract	Concrete	Total
Initial short lists	19	42	61
Before manual filtering	909	1,594	2,503
After manual filtering: removing non-nouns, repetitions, errors, etc.	<b>189</b>	<b>180</b>	<b>369</b>

Table 2. Manual extension of the initial short list.

The next step was to automatically extract, for each of these 369 words, the 50 nearest neighbors and 50 syntactic co-occurrences obtained from the resource Les Voisins De le Monde<sup>3</sup> and to compare the output of each approach (a sample of the list can be found in the Appendix B).

## 4. Results and Discussion

### 4.1 Results

From the list of 369 words we gathered a quantitatively different output among the categories: 62,174 abstract words and 31,333 concrete words, which means that the number of concrete words gathered with nearest neighbors and syntactic co-occurrences is half the number of the gathered abstract words. After eliminating all the repetitions, we obtained 4,222 unique concrete words and 3,676 unique abstract words, as shown in Table 3:

Category	Abstract	Concrete	Total
Raw list	62,174	31,333	93,507
Filtered data	3,675	4,223	<b>7,898</b>

Table 3. Number of abstract and concrete annotated words automatically obtained from the initial lists.

These figures show that it seems easier to obtain abstract nouns than concrete nouns straight away. This is not because there is a larger number of abstract words in French but rather because of the closeness of abstract concepts in context. In other words, if we choose a pair of random abstract nouns X and Y and a random pair of concrete words Z and W, a random abstract word X is more likely to have another random abstract word Y as a nearest neighbor or as a syntactic co-occurrence, than a random

pair of concrete words Z and W to appear in the same semantic network as nearest neighbors or semantic co-occurrences.

Differences between the two distributional approaches, nearest neighbors and syntactic co-occurrences, were also found. For concrete nouns, the output obtained through the nearest neighbors and syntactic co-occurrences is almost equal (cf. Table 4), but for abstract nouns these numbers are uneven (45,340 vs 16,834). Nearest neighbors is the method that worked better for abstract words quantitatively, and syntactic co-occurrences is the method which, as we observed in the processed dataset, worked slightly better for concrete words. This result confirms the hypothesis that there are differences in the semantic representations between concrete and abstract words.

Category	Abstract	Concrete	Total
Raw data nearest neighbors	45,340	16,223	61,563
Raw data co-occurrences	16,834	15,110	31,944
Filtered data nearest neighbors	<b>2,129</b>	1,631	3,760
Filtered data co-occurrences	1,546	<b>2,592</b>	4,138

Table 4. Number of abstract and concrete words obtained after bootstrapping from the experimental list using two different distributional methods.

After filtering the lists (removing repetitions and part-of-speech errors), the differences among the categories were narrow: we finally obtained 3,675 abstract and 4,223 concrete nouns.

### 4.2 Evaluation

We used an online platform to annotate through crowdsourcing a sample of 120 nouns randomly selected from the filtered data obtained after the extension of the list of 369 nouns: 60 concrete nouns (30 nearest neighbors and 30 syntactic co-occurrences from the initial list of 180 concrete nouns) and 60 abstracts (30 nearest neighbors and 30 syntactic co-occurrences from the initial list of 189 abstract nouns). The sample was randomly selected from the data to avoid sampling bias.

By means of an online questionnaire addressed to Aix-Marseille Univ. staff and students, the participants had to annotate each word using a slider scale between -100 (very abstract) on the left of the interface and 100 (very concrete) on the right (see Figure 1). Participants were advised not to use the ‘both concrete and abstract’ option in the middle of the scale (position 0) very often (those who did it were automatically excluded from the experiment by the system).

4 word-fillers were also added to the 120 stimuli: 2 abstract words with a low score of iconicity (‘haine’ and ‘espoir’, hatred and hope, respectively) and 2 concrete words with a high score of concreteness and iconicity (‘ananas’ and ‘guitare’, pineapple and guitar). This is a common precaution to know if the participant has understood the instructions and if he has accomplished the task honestly

(the annotations of these words are not considered in the evaluation). In the instructions for the participants at the beginning of the test, we advised to make an intuitive choice without overthinking. 1,083 individuals participated in the test in only 4 hours (after this period the link to the platform was disabled).

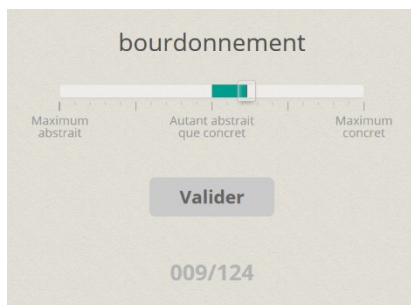


Figure 1: Screenshot of the test online (for the word ‘bourdonnement’, buzz).

The results of the annotations were subjected to statistical analysis with R. All the choices lower than 0 were considered as choices towards ‘abstractness’ and all the choices higher than 0 were considered as choices towards ‘concreteness’. This scale allows us (i) to observe the degree of these notions according to human judgment and (ii) to identify polysemic words (we hypothesize that polysemic words are close to 0 values). Human annotations were compared with the results of the automatic annotation on a binary basis. To convert the data gathered from the annotation, the means for each stimulus were calculated based on the 1,083 responses.

Starting from the fact that the semantic decision task is complex and ambiguous even for a human, we obtained better agreements with the method of nearest neighbors. For both methods, the correspondences were better for concrete than for abstract words, as it is showed in Table 5.

Category	Abstract	Concrete	Total
Nearest Neighbors	21 out of 30	25 out of 30	
Precision score	<b>70%</b>	<b>83,3%</b>	<b>77 %</b>
Syntact. Co-occurrences	15 out of 30	19 out of 30	
Precision score	50%	63,3%	57 %

Table 5. Number of correspondences human judgement/automatic annotation and Precision.

The standard deviation of human annotations was large which further confirms the difficulty of the task and the importance of our results. The stimuli with the smaller standard deviations ( $< 40$ ) were all concrete names, among the stimuli with the larger standard deviations ( $> 65$ ) there were abstract nouns and polysemic concrete names. We observed a strong correlation ( $r = -0.6210$ ) between the means of stimuli (degree of concreteness) and the standard deviation (hesitation level): the greater the degree of concreteness, the lower the value of standard deviation. In general, the more a word is considered as concrete, the less hesitations appear during the annotation.

Using Fleiss’ kappa formula, we obtained an inter-annotator agreement equal to 0.256, which is a weak agreement, but in line with other experiments on lexical

semantic decision, particularly with a large scale from -100 to 100.

Our data analysis revealed that in the case of polysemy, a person chooses a concrete meaning rather than an abstract one, which is consistent with another research (Kwong, 2013). For example, the words ‘cadre’, ‘échelle’, ‘cote’, ‘espèce’, ‘réserve’, ‘secours’ (frame, scale, rating, specie, reserve, rescue) were classified as concrete.

We investigated the influence of the frequency of individual words on our results, but we did not find any relationship between frequency and means ( $r = -0.0039$ ), and frequency and standard deviation ( $r = -0.0901$ ). Finally, the results from two groups of participants (not native French speakers and participants with speech or language problems) were analyzed apart, however no significant differences were found in the results from these two groups and the others.

### 4.3 Discussion and future work

Since the nearest neighbors method showed its performativity in the task of automatically expanding the initial list of words and confirmed its conformity to a human’s judgment at a fairly high level (77 % compared to the overall 57 % of syntactic co-occurrences), we plan to continue to use this distributional method in order to enlarge the list of 7,898 words already obtained. It will be also interesting to compare the results with results obtained with word embeddings.

The present list and its enlarged versions will also be integrated into the lexical resource ReSyf to be used in a text simplification system. It will also be utilized to future studies on the impact of word concreteness/abstractness in the reading process in normal and poor readers, and people with reading disabilities. These studies can be relevant for French, as previous researches have been mostly conducted for English (Sandberg & Kiran, 2014; Crutch & Warrington, 2005; Kiran et al., 2009; Palmer et al., 2013; Schwanenflugel & Stowe, 1989; Schwanenflugel et al., 1988).

## 5. Conclusion

Guided by the idea that abstract and concrete words have different semantic organizations, in this paper we confirmed our first hypothesis: abstract nouns are semantically linked to other abstract nouns and concrete nouns are semantically linked to concrete nouns in context. We also verified that nearest neighbors and syntactic co-occurrences methods work differently depending on the concreteness of the word. We found differences in the two approaches explored: nearest neighbors permitted to obtain more abstract nouns, while for concrete nouns both nearest neighbors and syntactic co-occurrences showed similar results from a quantitatively point of view. However, after removing repetitions, we obtained two lists of almost equal size, even if we finally gathered more concrete words.

These results would suggest that abstract words have a richer semantic network (i.e. more words in common) than concrete words. The difference between nearest neighbors and syntactic co-occurrences methods shows that the

nearest neighbors method seems more suited for gathering abstract words, while the syntactic co-occurrences method seems more suitable to enrich a list of concrete words (see Table 4).

Having compared the sample from our automatically annotated data with the results of human evaluation, we conclude that the nearest neighbors method shows better precision rates for both abstract and concrete words. Annotating concreteness is prevalent using both methods according to human judgement, which can be related to the fact that in case of polysemy a participant is more likely to choose a concrete meaning than an abstract one.

In future work, we plan to continue the extension of the existent list with the nearest neighbors method and compare the results with other methods such as word embeddings. Besides, we foresee to study abstract and concrete words in authentic texts to evaluate their impact on reading (e.g. in primary schools with different reader profiles). In doing this, we aim to verify to what extent the 'concreteness effect' impacts word reading and comprehension in beginning readers of French.

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## Appendix A. Initial short lists.

19 Abstract words of the initial list (Ferrand, 2001)		42 Concrete words of the initial list (Ferrand and Alario, 1998)			
amitié	joie	arbre	chat	livre	poignée
colère	peur	avion	chemise	main	poisson
courage	santé	bateau	cheval	maison	porte
crainte	sécurité	boîte	chien	manteau	pomme
effort	siècle	bouteille	cigarette	marteau	robe
espoir	succès	bras	église	montagne	sucre
gloire	tristesse	bureau	ferme	montre	table
haine	usage	café	feuille	mur	téléphone
idée	vérité	camion	fleur	oiseau	train
imagination		carte	journal	pain	voiture
		chaîne	lettre		

## Appendix B. Examples from filtered data.

The ‘relation’ is the method by which a word has been obtained: nearest neighbor (NN) or syntactic cooccurrence (SC). The category corresponds to concrete (C) and Abstract (A) nouns, we note with \* the errors from the automatic annotation.

Id Stimulus	Stimulus	Id Output	Output	Relation	Category
1	aéroport	1	port	NN	C
1	aéroport	2	gare	NN	C
1	aéroport	3	parc	NN	C
1	aéroport	4	station	NN	C
1	aéroport	5	tarmac	SC	C
1	aéroport	6	atterrissage*	SC	C
1	aéroport	7	ravitaillement*	SC	C



1	aéroport	8	airbus	SC	C
2	ballon	9	balle	NN	C
2	ballon	10	objet	NN	C
2	ballon	11	vélo	NN	C
2	ballon	12	cassette	NN	C
2	ballon	13	nacelle	SC	C
2	ballon	14	manieur	SC	C
2	ballon	15	tour	SC	C
2	ballon	16	tentative*	SC	C
3	câble	17	téléphone	NN	C
3	câble	18	bouquet	NN	C
3	câble	19	télécommunication*	NN	C
3	câble	20	satellite	NN	C
3	câble	21	abonné*	SC	C
3	câble	22	gaine	SC	C
3	câble	23	abonnement	SC	C
3	câble	24	raccordement	SC	C
4	dessin	25	photo	NN	C
4	dessin	26	photographie	NN	C
4	dessin	27	peinture	NN	C
4	dessin	28	portrait	NN	C
4	dessin	29	ensemble	SC	C
4	dessin	30	dossier	SC	C
4	dessin	31	carton	SC	C
4	dessin	32	accompagné*	SC	C
5	abus	33	recel	NN	A
5	abus	34	détournement	NN	A
5	abus	35	escroquerie	NN	A
5	abus	36	fraude	NN	A
5	abus	37	information	SC	A
5	abus	38	complicité	SC	A
5	abus	39	rencontre	SC	A
5	abus	40	juge*	SC	A
6	chance	41	possibilité	NN	A
6	chance	42	capacité	NN	A
6	chance	43	avantage	NN	A
6	chance	44	potentiel	NN	A
6	chance	45	scepticisme	SC	A
6	chance	46	égalité	SC	A
6	chance	47	égalité	SC	A
6	chance	48	illusion	SC	A
7	décision	49	choix	NN	A
7	décision	50	mesure	NN	A
7	décision	51	accord	NN	A
7	décision	52	déclaration	NN	A
7	décision	53	félicité	SC	A
7	décision	54	cassation	SC	A
7	décision	56	pourvoi	SC	A
7	décision	57	réaction	SC	A
8	émotion	58	inquiétude	NN	A
8	émotion	59	angoisse	NN	A
8	émotion	60	sentiment	NN	A
8	émotion	61	plaisir	NN	A
8	émotion	62	capteur*	SC	A
8	émotion	63	chantage	SC	A
8	émotion	64	larme*	SC	A
8	émotion	65	moment	SC	A