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Can we predict self-reported customer satisfaction from interactions ?

Jeremy Auguste, Delphine Charlet, Geraldine Damnati, Frédéric Béchet,
Benoit Favre

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(1) {firstname.lastname}@univ-amu.fr
(2) {firstname.lastname}@orange.com

Summary

- **Objective:** Automatically evaluate the customer satisfaction from conversation logs.
- **Data:** Contact center chat conversations and the customers' satisfaction surveys.

- **Method:** Comparison of different classification schemes: 3-labels, 2 × 2-labels or 2-labels multitask classification. Definition of the Serious Error Rate metric to focus on problematic confusions.
- **Results:** Considering the classification of extreme opinions as two distinct tasks greatly improves the results on the neutral class.

Task and Motivations

Task: Evaluate the customer satisfaction from the logs of a human-human conversation.

Possible evaluations: Direct supervision using surveys filled by the customers themselves and indirect supervision by experts.

Problem: Customer surveys are not mandatory and experts can't evaluate every conversation.

Question: Can we retrieve directly from conversation logs such subjective opinions as the *Net Promoter Score* ?

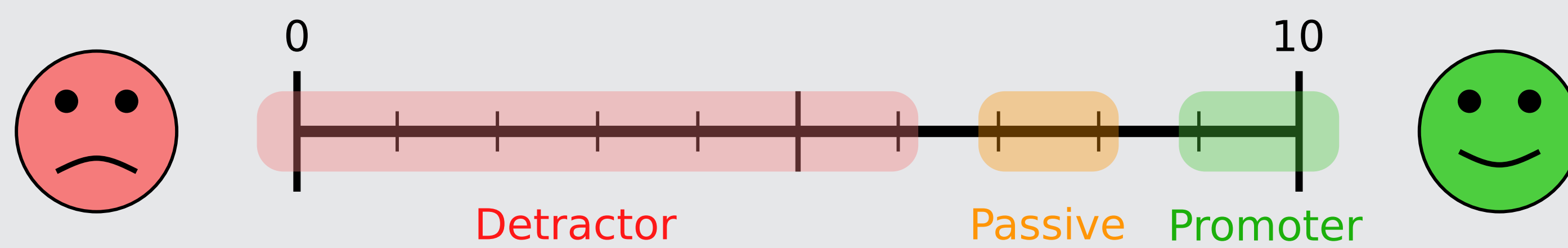
Orange conversation corpus

Chat data description:

- Technical and commercial assistance;
- 79,000 conversations with completed surveys;
- 140,000 unique tokens;
- Word Error Rate of 4.3% overall (10.1% for the *Customers*, 1.6% for the *Agents*)

Customer surveys

How likely would you be to recommend us to your family and friends ?

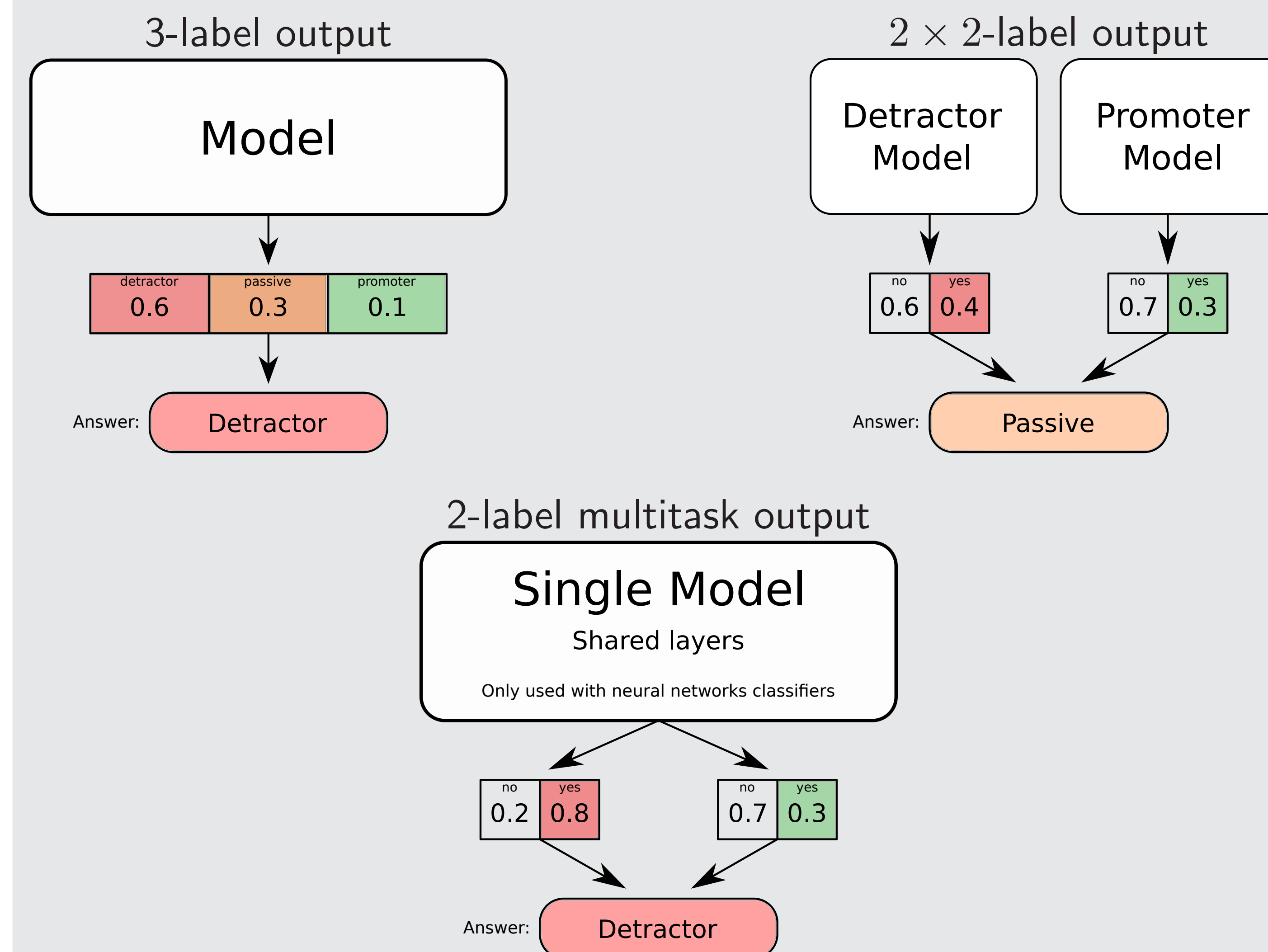


Following Customer Relationship Management conventions, appreciations are grouped into 3 categories: **detractor**, **passive** and **promoter**.

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Classification schemes



Goal: Avoid confusions between **detractors** and **promoters**.

Classifiers

Different classification methods that consider dialogues differently:

- Support-Vector Machine (SVM);
- Convolutional Neural Network (CNN);
- Long-Short Term Memory network with attention (RNN).

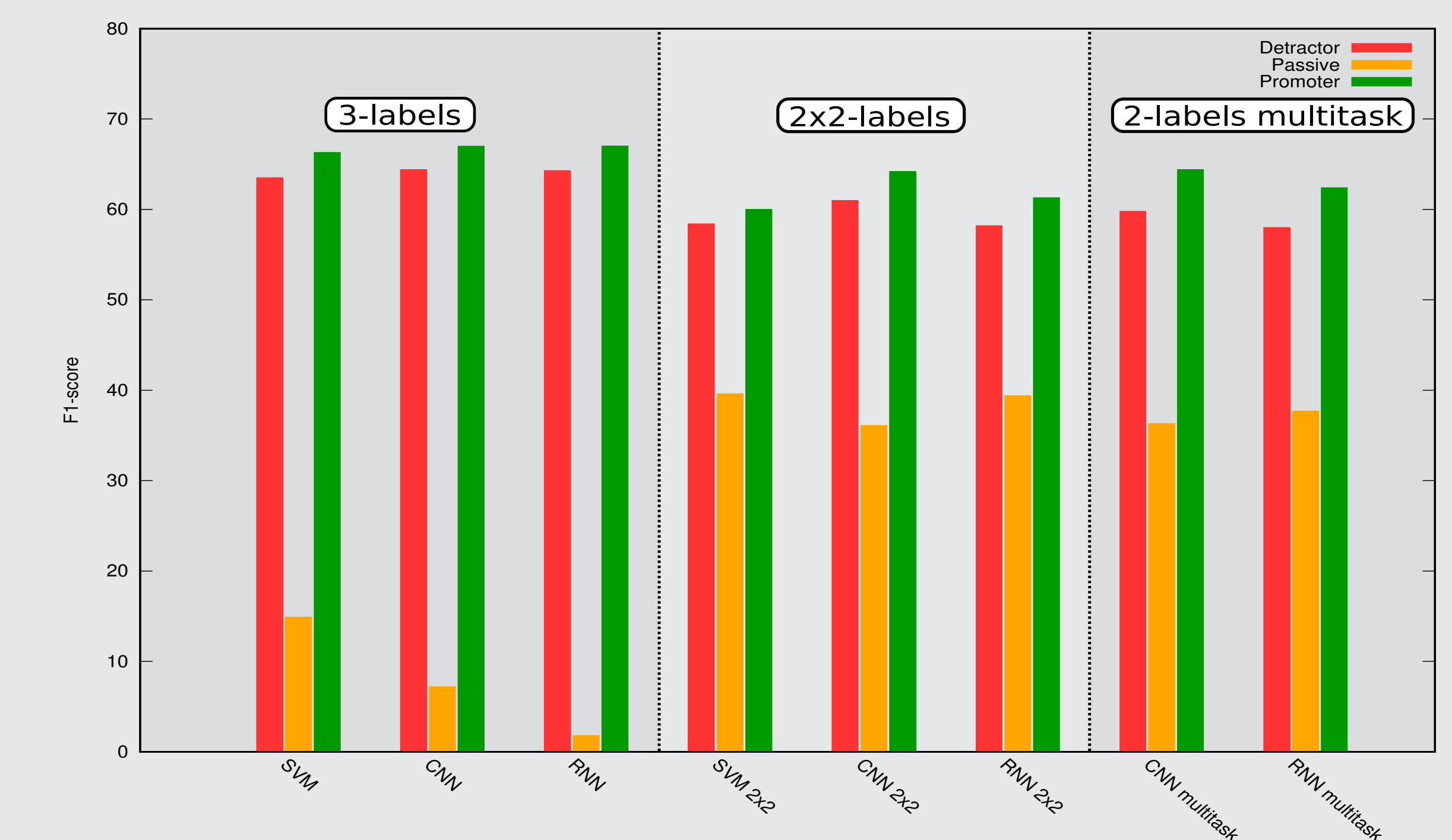
Evaluation metrics

Use of 3 different metrics:

- **Accuracy:** $\frac{\#correct\ predictions}{\#samples}$,
- **F1-score:** $F1(l) = \frac{2 \times Precision(l) \times Recall(l)}{Precision(l) + Recall(l)}$,
- **Serious Error Rate:** Percentage of confusion between the **Detractor** and the **Promoter** classes.

Results

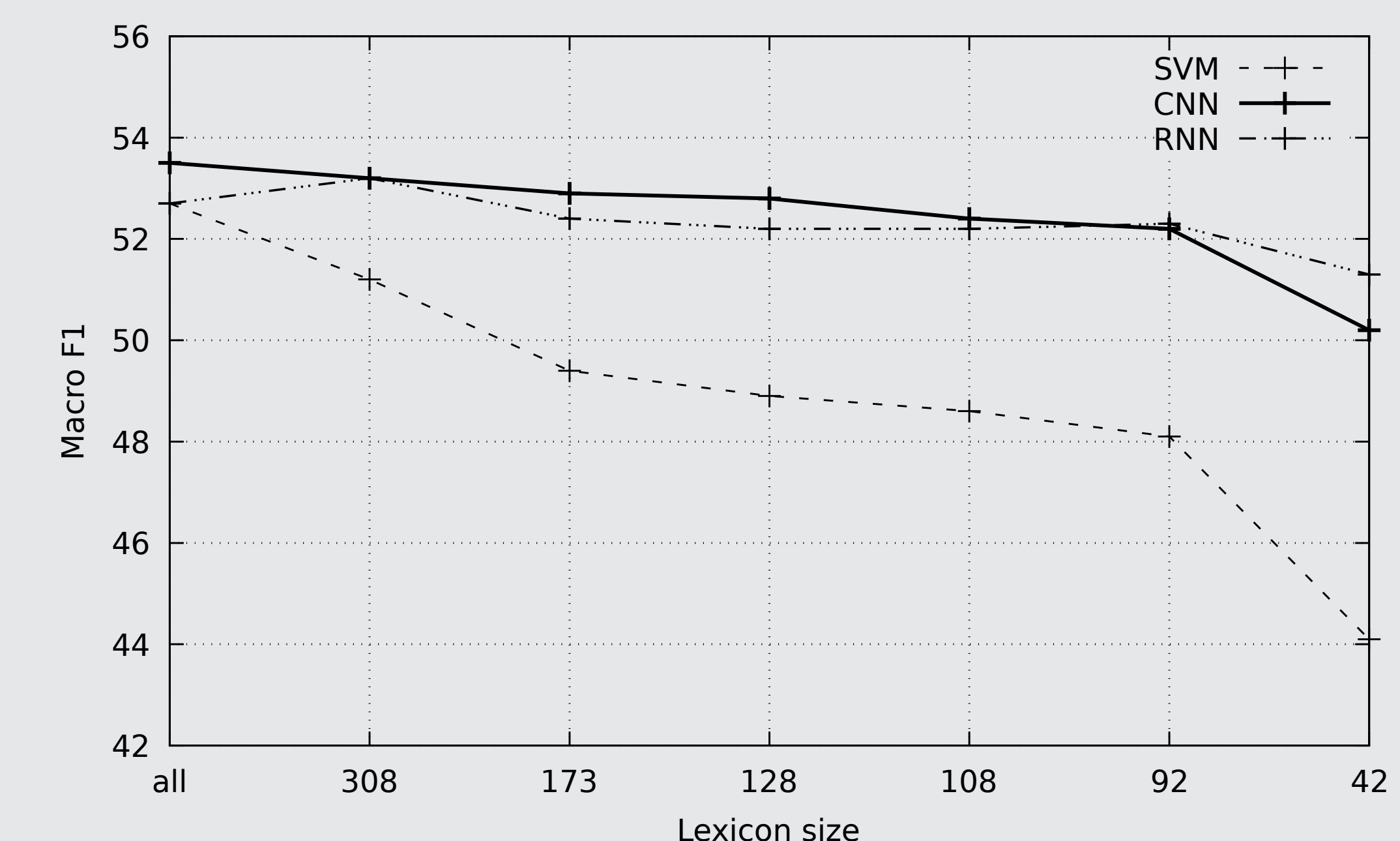
Model	Accuracy	Serious Error Rate
<i>3-labels classification scheme</i>		
majority class	42.7	30.9
SVM	56.9	14.7
CNN	57.5	15.5
RNN	57.5	15.8
<i>2-labels+reject classification scheme</i>		
SVM 2x2 labels	52.7	6.2
CNN 2x2 labels	55.2	7.7
CNN 2 labels multitask	55.0	7.6
RNN 2x2 labels	53.5	6.5
RNN 2 labels multitask	53.5	6.5



2-labels schemes greatly improve the prediction of the passive class and greatly reduce confusions between extreme classes.

Contrastive experiment

Reducing the lexicon size to evaluate domain robustness:



Lexicon reduced by selecting words occurring at least 10K to 100K times.