Model details

Goal

- 600,000 queries
- 1,500 categories
- A query is a sequence of words
- A query belongs to a category

- Goal :
  - Predict the category of a query

Not a trivial ML problem

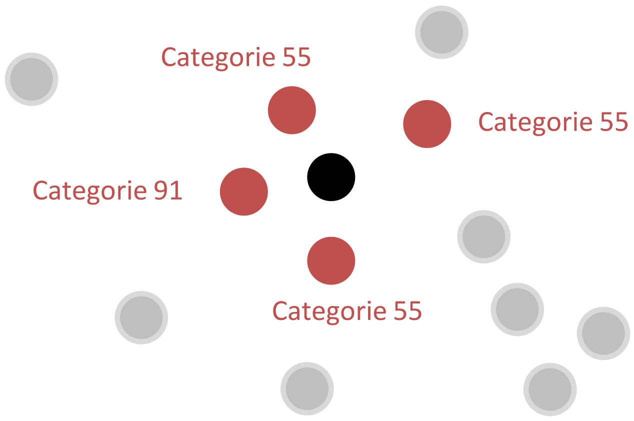
- Sparsity of data
  - 70,000 words as features
  - A query has only few words
- Skewed distributions
- 1,500 different outcomes
- Conclusion
  - Logistic regression, Boosting trees might not do the job

KNN, overview

- In such a case, from XP
  - KNN might be a good fit

- Basic ideas behind KNN algorithm
  - For a query target :
    1. Extract the TOP N closest queries in the training set
    2. Compute « category » distribution among the TOP N
    3. Pick up the mode’s distribution as the prediction

KNN, overview



- Query Target
- TOP N closest queries
  - **Catégorie 55 : ¾**
  - Categorie 91 : ¼
- Prediction of Query Target :
  - **Catégorie 55**

KNN, similarity

- What *close to* means?
  - Need a similarity measure

- Similarity between a and b :
  - $S(a, b) = \sum P_{w_i}$
  - W_i, the words shared by a and b
  - P_{Wi}, the Disciminant Power of word i

KNN, similarity

Query a : **the jordan game** tickets

Query b : **the game** of **jordan** book

Words W_i : **jordan , game , the**

500 100 25

Discriminant Power of the word ‘game’

S(a,b) : 500 + 100 + 25 = 625

KNN, similarity

- We prefer to normalize the similarity
  - We will use the maximum similarity possible to normalize the score
  - $S_n(a,b) = \left(\frac{S(a,b)}{S(a,b)MAX}\right)$

Query target : the jordan game tickets

25 500 100 175

A query should contains the words [*the,jordan,game,tickets*] to
Get the maximum similarity with the query target.
In this case, the similarity will be **800** (25+500+100+175)

$$S_n(target,'\ game\ of\ jordan') = \frac{600}{800} = {}^{3}/_{4}$$

Discriminant Power, definition

- Discriminant Power, P_{wi} of the word i is :

- $P_{W_i} = \frac{p(prediction=TRUE\ |w_i)}{p(prediction=TRUE)}$

  - $p(prediction = TRUE\ |w_i) = \int p(c|w_i)^2 dc$
  - $p(prediction = TRUE) = \iint p(c|w)^2 p(w)\, dc\, dw$

Discriminant Power, justification

- Why? $p(prediction = TRUE\ |w_i) = \int p(c|w_i)^2 dc$

A random query comes in :

- I know it contains the word basket
- The probability it is of ‘Sport’ category is therefore 0.5
- The probability I will correct predict ‘Sport’ when it is actually ‘Sport’ is 0.5 * 0.5
- The probability I will correct predict any category is Sum(p(c|basket)²)

$p(c|basket)$

1. Sport : 0.5
2. Shopping : 0.3
3. News : 0.1
4. Book : 0.1

Discriminant Power, examples

- Othaheel : 1249
- Nuoma : 1275
- Oscars : 1050
- Fluorigard : 703
- Chunks : 406
- Positive : 206
- Maker : 94
- Low : 19
- The : ~1
- A : ~1
- For : ~1

Remark

- $p(c|w_i)$ is not that trivial to compute

- Let's imagine only two categories A and B
  - 3 queries of category A containing the word 'covid'
  - 0 queries of category B containing the word 'covid'

- What is p(c=A|'covid')? 1?
- What is p(c=B|'covid')? 0?

- We know it is not a good approximation

Remark

- $p(c|w_i)$ is not that trivial to compute

- To solve this problem, we used Bayes Theorem

- To not spend too much time on it, please go and see my solution to a very similar problem

Picking Candidates Strategy, motivation

- How to find the top N closest queries to a query target?
  - Compute similarity with all the queries except the target?
    - 600,000 queries , the cost would be too high
  - Compute Similarity with the candidate queries (sharing the same words)?
    - ~3,000 queries on avg, the cost would be better but still very high
- **Idea** : looking for the best queries first

Picking Candidates Strategy, details

- Rank the structure of potential closest queries

- Look first in the best set of potential queries
  - Then look for the second best
  - And so on …
  - Stop when you got enough*

** The only hyperparameter of the model*

Picking Candidates Strategy, example

Query Target : **jordan** game ticket

500 100 250

The query that is the closest to the query target should contains

- The words : *jordan, game, ticket*
- It would give a maximum similarity of **850**, (relative score of 1)

Set of potential queries ranking

1. 850 (1.00) : *jordan, ticket, game*
2. 750 (0.88) : *jordan, ticket*
3. 600 (0.70) : *jordan, game*
4. 500 (0.58) : *jordan*
5. 350 (0.41) : *ticket, game*
6. 250 (0.29) : *ticket*
7. 100 (0.12) : *game*

Picking Candidates Strategy, hyperparameter

Set of potential queries ranking

1. 850 (1.00) : *jordan, ticket, game*
2. 750 (0.88) : *jordan, ticket*
3. 600 (0.70) : *jordan, game*
4. 500 (0.58) : *jordan*
5. 350 (0.41) : *ticket, game*
6. 250 (0.29) : *ticket*
7. 100 (0.12) : *game*

Hyperparameter = 0.95
gives the best results

We stop looking for other queries when :

- (relative score) < **hyperparameter value**
- AND
- Number of queries reached so far > 0
  - If Number of queries reached so far = 0:
    - Continue to the next set

Picking Candidates Strategy, benefice

- With this strategy :
  - No need to collect candidates anymore
    - Retrieve directly the top N queries according to hyp
  - Therefore, only looking for ~15 queries VS ~3,000

Remark

- What if a query target does not contains a known word?
  - Then, we assume we know nothing about this query
  - So, we will pick the most frequent category as prediction