Userless Classificaton for the Yelp Dataset Challenge

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Abstract

We planned on building latent features from the text reviews which would depict the cat- egories of the business. To put it in a nutshell, we would like to build from the text reviews of an entry a vector representation which carries local geometry information. Once we built the document-term matrix containing the words count of the reviews for each business (the reviews are aggregated over each restaurant), we could simply use a matrix factorisation on the counts . To be able to interpret the latent features as topics, we could use a Non-negative matrix factorization (the possible negative features in the SVD cannot stand for cluster as- signement). A finer result can be reached with the use of a generative probabilistic model, thatâĂŹs why we chosed the latent dirichlet allocation. The LDA uses a Dirichlet prior on the words distribution over the topics and on the topics distribution over the document which will gives them more freedom than the deterministic approach of the NMF.

1. Introduction

The classification system in Yelp is manual. When the owner of a business creates a page for his restaurant or bar, he is asked to enter a certain number of attributes or "tags". Yelp users can then alter or even add some new tags based on their experiences. As part of the Yelp Data Set Challenge Round 6, we decided to tackle the issue of classification with ultimate objective to be able to create an automatised method to classify venues, based on the information contained on the business' web page and most importantly the written reviews from Yelpers.

This project can be divided in two parts, the first on feature extraction and the second on classification and clustering. In more details, we applied various dimensionality reduction methods such as Latent Dirichlet Allocation (LDA) or Non-negative Matrix Factorisation (NMF) to embed the reviews into a geometrical space. We then decided to compare both supervised approaches such as Multinomial Regression and unsupervised approaches, using the Walktrap algorithm, to the problem of classification on the Yelp dataset.

2. Data

Yelp provides data on all kinds of venues such as dentists or bars in 5 cities in the United-States and Europe. The data can be summarised as follows:

- 1.6 million reviews
- 61 000 businesses
- 481 000 attributes
- aggregated check-in measurements over time

For simplicity, we chose to focus on restaurants and bars in the city of Las Vegas, Nevada. We reduced the data to a dataset of 3822 businesses, about 20 thousands reviews and 250 other features such as hours, parking availabity, take-out, ambience. If the numerical data we received from Yelp was mostly cleaned, it was not the case of the text data. Cleaning the reviews represented a significant part of this final project. We present some of the steps we followed in the process:

- We aggregated all the reviews about a particular business into a "super" review, in order to get a general sense of what the restaurant was about,
- We applied spelling corrections, removed common stopwords and generic words such as "table" or "restaurants",
- We attempted at only selecting common words and not adjectives in order to focus on what the venues were about and not the users' opinions,
- We transformed the corpus of "super reviews" into a document-term matrix that we could exploit.

3. Feature Extraction

3.1. Approach

To extract content from the reviews, we applied 2 methods from Topic Modeling to reduce the document term matrix into meaningful information. We first looked at LDA, using both a Gibbs sampler and Online Variational Inference (OVI) algorithm. Note that we used the Gibbs sampler as a way to benchmark our coded OVI. The motivation behind OVI is twofold. First, it appeared more appropriate to the data we were working with, indeed new reviews can always be added to the corpus in continuous flow. Second, it showed some extremely significant time improvement over the Gibbs sampler version in Python (cf figure 1). We also wanted to compare the performance of LDA with a non-probabilistic approach which is NMF.

3.2. Latent Dirichlet Allocation

The LDA is a three-level hierarchical Bayesian model. The basic idea that documents are represented as random mixtures over latent topics and each topic is characterized by a distribution over words.[1]

The generative process for a document **w** in a corpus D is the following:

1. Choose the topics representation: $\phi \sim \text{Dir}(\beta)$
2. Choose the number of words: $N \sim \text{Poisson}(\xi)$
3. Choose the distribution of topics: $\theta_w \sim \text{Dir}(\alpha_w)$
4. For each of the N words:
   (a) Choose a topic assignement: $z_{n,w} \sim \text{Multinomial}(\theta_w)$
   (b) Choose a word: $w_n \sim \text{Multinomial}(\phi_{z_{n,w}})$

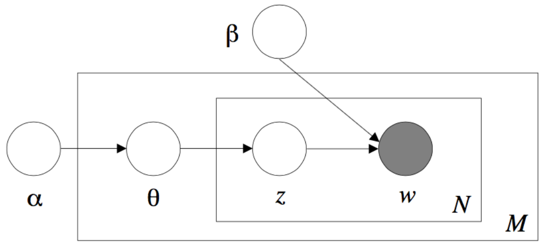


Figure 1: *Graphical Model Representation of LDA*

3.3. Parameter Estimation and algorithm:

The main issue relies in computing the posterior distribution of the hidden variables given a document:

$$p(\theta, \mathbf{z}|\mathbf{w}, \alpha, \beta) = \frac{p(\theta, \mathbf{z}, \mathbf{w}|\alpha, \beta)}{p(\mathbf{w}|\alpha, \beta)}$$

This distribution is intractable. As mentioned above, we used two methods to infer it: through a Gibbs sampler or variational inference. In the first case, we are estimating the hyper parameters θ and ϕ with samples on the different variables. Alternatively, we chose the online variational inference method which finds the variational parameters that optimize a lower bound on the loglikelihood. The setup [2] of the Variational Inference is as follows. We first approximate the true posterior by a simpler and factorised distribution:

$$q(\boldsymbol{z}, \boldsymbol{\theta}, \boldsymbol{\beta}) = q(\boldsymbol{z})q(\boldsymbol{\theta})q(\boldsymbol{\beta})$$

where:

$$q(z_{di} = k) = \phi_{d_{w_{di}k}} \quad q(\theta_d) = \text{Dir}(\theta_d, \gamma_d) \quad q(\beta_k) = \text{Dir}(\beta_k, \lambda_k)$$

The γ parameter rule the topic assignments for each document and the $\boldsymbol{\lambda}$, the topics themselves. We then minimise the KL divergence between the distribution q and the true posterior p like for the usual variational inference. What differs in online variational inference is that we sample a batch of document at each step and perform the E-step as if this batch constituted the entire corpus. We present the algorithm below:

Algorithm 1 Batched Online Variational Inference

```
1:  Define $\rho_t \equiv (\tau_0 + t)^{-\kappa}$
2:  Initalise $\boldsymbol{\lambda}$ randomly
3:  Sample a batch $\mathcal{S}$ of documents of size S
4:  for $t$=0 to $|D|/|\mathcal{S}|$ do
5:      for $d$ in $\mathcal{S}$ do
6:          while $\gamma_(d)$ hasn't converged do
7:              Set $\phi^{(d)}_{twk} \propto \exp\{\mathbb{E}_q \log \theta_{tk} + \mathbb{E}_q \log \beta_{kw}\}$
8:              Set $\gamma^{(d)}_{tk} = \alpha + \sum_w \phi^{(d)}_{twk} n_{tw}$
9:          Compute $\tilde{\lambda}_{kw} = \eta + \frac{D}{S} n_{tw} \phi^{(d)}_{twk}$
10:     $\boldsymbol{\lambda} = (1 - \rho_t)\boldsymbol{\lambda} + \rho_t \tilde{\boldsymbol{\lambda}}$
```

where $\kappa \in (0.5, 1]$ rules how fast we forget old values of $\tilde{\lambda}$ and τ_0 how much weight one wants to put on the first iterations.

3.4. Evaluation Method

We need a measure to evaluate the performance of our model and to tune the hyperparameters. We use perplexity on held-out data as a measure of our model fit. Perplexity is defined as the geometric mean of the log likelihood of the words in the held-out set of docuements given the trained model. In our case, for each document we held out 20% of the words which constitue the test set.

$$perplexity(D_{test}) = \frac{\sum\limits_{d \in D_{test}} \log p(words)}{\sum\limits_{d \in D_{test}} |d|}$$

$$perplexity(D_{test}) = \frac{\sum\limits_{d \in D_{test}} \sum\limits_{w \in d} \log \left(\sum_{t \in topics} p(w|t)p(t|d) \right)}{\sum\limits_{d \in D_{test}} |d|}$$

We used this measure to optimize the number of topics K and the hyper parameters of the optimization. We also used the perplexity on the training set to benchmark our algorithm with the Gibbs sampler in the LDA 1.0.3 package in Python:

$$\text{perp}_{OVI} = -6.78 \quad \text{and} \quad \text{perp}_{GS} = -6.45$$

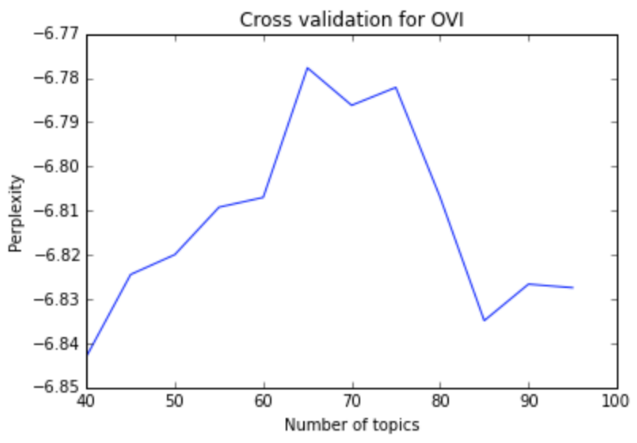
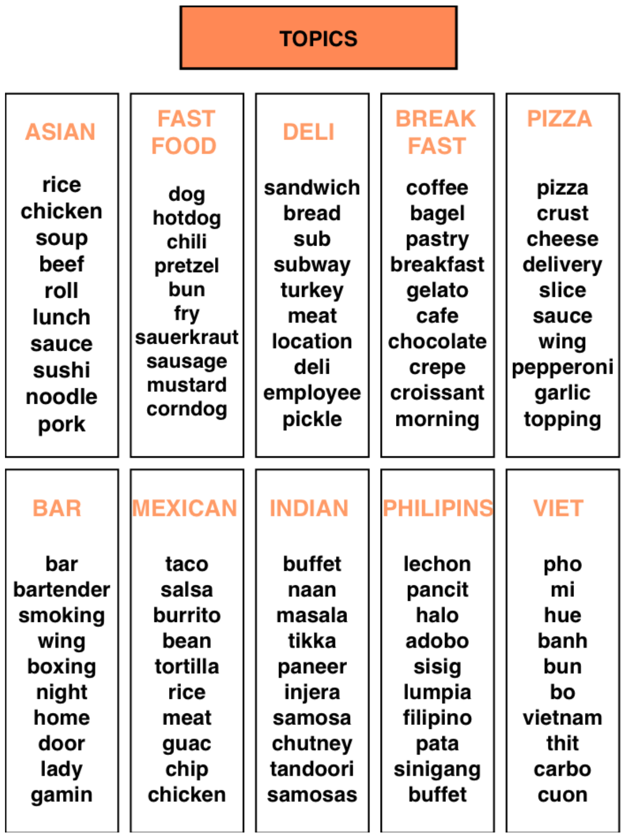


Figure 2: *Cross Validation over the number of Topics*

3.5. Results

Another way to assess the performance of our LDA was to inspect the topics outputted by the algorithm. We present some of the most significant topics:



TOPICS

ASIAN	FAST FOOD	DELI	BREAK FAST	PIZZA
rice	dog	sandwich	coffee	pizza
chicken	hotdog	bread	bagel	crust
soup	chili	sub	pastry	cheese
beef	pretzel	subway	breakfast	delivery
roll	bun	turkey	gelato	slice
lunch	fry	meat	cafe	sauce
sauce	sauerkraut	location	chocolate	wing
sushi	sausage	deli	crepe	pepperoni
noodle	mustard	employee	croissant	garlic
pork	corndog	pickle	morning	topping

BAR	MEXICAN	INDIAN	PHILIPINS	VIET
bar	taco	buffet	lechon	pho
bartender	salsa	naan	pancit	mi
smoking	burrito	masala	halo	hue
wing	bean	tikka	adobo	banh
boxing	tortilla	paneer	sisig	bun
night	rice	injera	lumpia	bo
home	meat	samosa	filipino	vietnam
door	guac	chutney	pata	thit
lady	chip	tandoori	sinigang	carbo
gamin	chicken	samosas	buffet	cuon

Figure 3: *Topics extracted from the Las Vegas reviews using OVI*

We obtained similar results using the NMF approach. The topics themselves were not our primary interested. As mentioned in the introduction, we were using these methods primarly for dimensional reduction purposes.

We would like to also make a general comment about the Online Variational algorithm. We noticed that the OVI algorithm is extremely sensitive to the hyperparametrisation, i.e the batch size S, the forgetfullness parameter κ and the early iterations weith parameter τ. This was also noted by Tamara Broderick, Nicholas Boyd, Andre Wibisono and Ashia C. Wilson in their paper[3]. In addition to validating the number of topics, validating over these parameters was crucial to obtain valuable resutls.

We now present two different approaches to answer the question of classification using supervised and unsupervised machine learning.

4. Supervised Classification

Once the feature have been extracted, we can apply supervised learning methods to classify the Yelp restaurants considering the category labels as output. Several approaches are possible to solve this multi-labels classiffication task depending on the nature and patterns of the features.

4.1. Approach

The features are divided into two main parts: on one hand, the topics assignements extracted from the reviews with the LDA and on the other hand, the properties provided by Yelp. Pre-processing the latter part provided a 198 dimensional vector. These features contain both numerical values (rating, space coordinates, number of reviews, customer check-in...) and categorical ones which we converted into indicator variables.

Given our numerical features, many different discriminative and generative models could be appllied on our data. Nonetheless, the indicator features are sparse and the data are really noisy. We need to consider a penalized or aggregated model to reduce overfitting.

We chose a one-vs-all approach to tackle this multi-labels task where we build one binary classifier for each label. We then assign to the entries the labels predicted by each model. The goal is here to explore how the different models perform and to tune them to come up with the best estimator. We developped our own l2 penalized logistic regression and used sklearn for the other models.

4.2. Results

Dimensionality Reduction We decided to reduce the dimension of the dataset before applying our model. We used it only on the customer check-ins counts to embed them in an euclidean space. We chose to project them because they already shared a common structure. Then, the combination of the embedded features with the latent features provided by the reviews is more consistent. We chose to apply it while keeping **95%** of the variance which reduces the dimension from **168** to **19**.

Models Evaluation Here we provide the different results we obtained from our models. We ran one-vs-one classifiers for the 10 different labels which are the most represented in the Las Vegas restaurants. Then we evaluated for each classifier its accuracy and averaged them to get the evaluation metric printed in the table. We tested them on three different kinds of features provided by the reviews depending on the method used to build them. Then we ran each model on the PCA projection and on the raw data. We provided for comparaison the baseline model where we do not assign any label. This result is really high because of the skewness of the considered sample, among the 10 categories considered for 3822 restaurants the most represented (Fast Food) contains 553 entries and the least (American New) 280 entries.

	OVI LDA	GS LDA	NMF
Baseline: all False	90,02 %	90.02 %	90.02 %
Kernel rbf SVM	90,81%	90.38%	90.38%
Kernel rbf SVM + PCA	90.83%	90.60%	90.57%
Logistic Regression	90.84%	91.89%	91.24%
Logistic Regression + PCA	92.59%	92.53%	92.68%
Lasso	90.82%	93.44%	92.01%
Lasso + PCA	93.44%	**94.46** %	93.08%
Random Forest	92.12%	93.58%	93.37%
Random Forest + PCA	92.84%	94.66%	94.06%

Figure 4: *Classification results for different features*

The first learning of this comparative study is the differences between each kind of feature. The models built with the GS features seems to outperform on average the two other which perform similarly to each other. These results are not surprising as the variationnal inference learns the closest model to the underlying one in terms of KL divergence. With the Gibbs sampling approach, we approximate the true underlying distribution at each iteration to refine our estimator. As a result, the latter method is by nature better to find the best model as long as it has enough iteration to converge and there actually exists an underlying mixture models. Nevertheless, the OVI remains a good proxy with regard to its time execution (53s against 50min for the Gibbs Sampler).

Then, if we compare the models to each other. The support vector machine performs poorly, the linear version was even closer to the baseline. This confirms that the data are not linearly separable and even their projection by the rbf function used in sklearn library (gamma function) is quite impossible to separate. The logistic regression performs better under the l1 penalization because of our sparse feature. Lastly, the random forest managed to reduce the common overfitting of the decision trees while aggregating them and provides on the PCA projection a very good estimator.

We plotted here the ROC curves of the Random forest for the 10 classes considered. The ranking of the area under the curve is almost the same that the descending ranking by number of positive elements for each classe.This shows that the more positive elements we have the better classifies the model. Nonethelless, trying to learn the model on a smaller and more balanced train set for the classes with a low number of positive elements does not improve the classification accuracy.

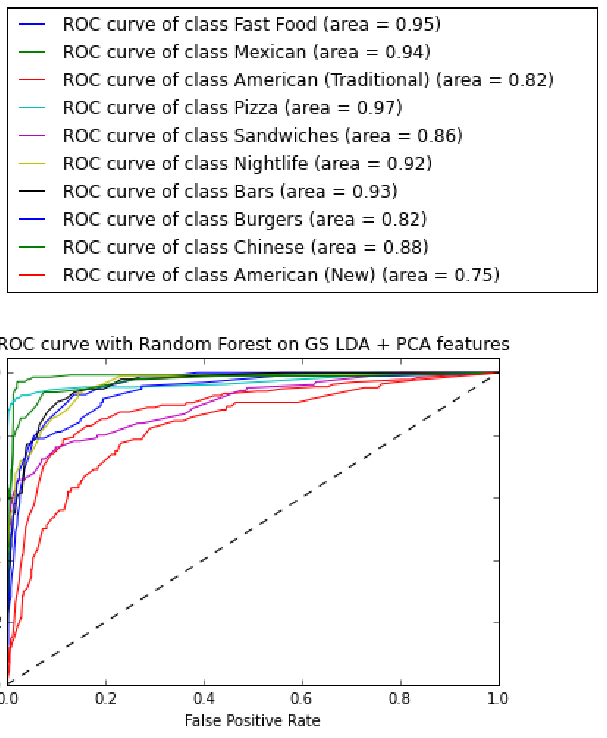


Figure 5: *Roc curve for the Random Forest one-vs-all classifiers*

TODO: analysis on the ROC curves

Feature Importance Once we found a sufficiently good estimator, we can investigate the weights it assigns to each feature. This could provide an answer to two important questions: *Are the feature extracted from the reviews more relevant than the one provided by Yelp to classify the restaurants by category? Among the features extracted by the review, can we identify for each category one or several highly discriminative features?* Moreover, we can compare the performance of the two different LDA we used.

We answer these questions with a comparative study on four specific categories (Fast Food, Pizza, Nightlife and Bars) with a Random Forest on four kinds of features, depending on the type of LDA used and the reduction with a PCA. The results with the features built with an NMF are similar to those with the OVI. We used the measure provided by scikit learn to evaluate the importance of the features. It is defined as the total decrease in node impurity averaged over all trees of the ensemble.

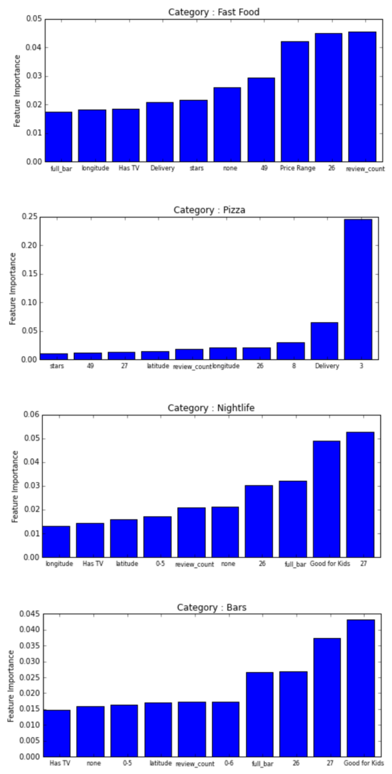


Figure 6: *Importance of the OVI LDA features in the one-vs-all Random Forest classification*

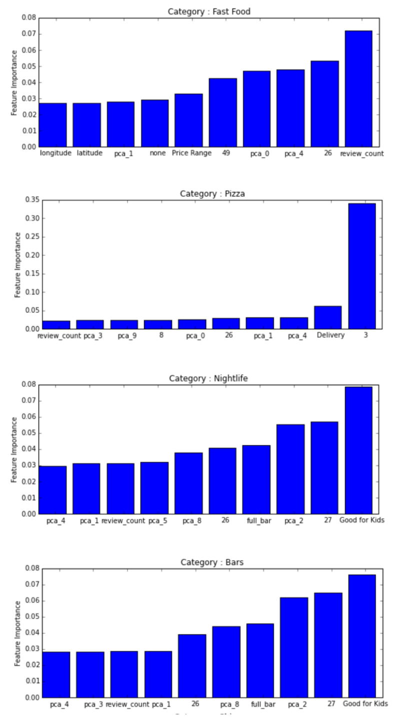


Figure 7: *Importance of the OVI LDA features with PCA in the one-vs-all Random Forest classification*

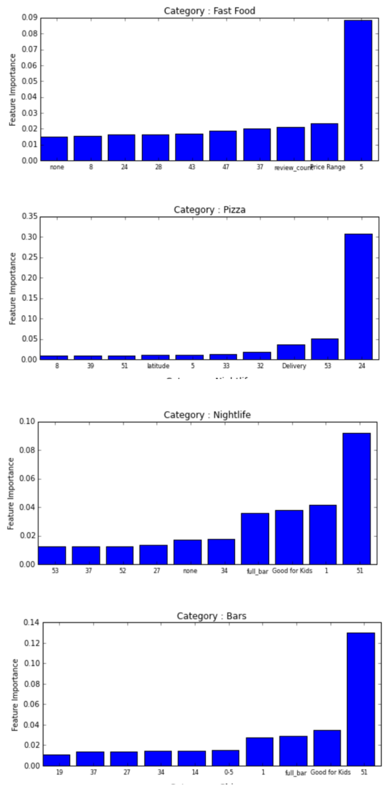


Figure 8: *Importance of the GS LDA features in the one-vs-all Random Forest classification*

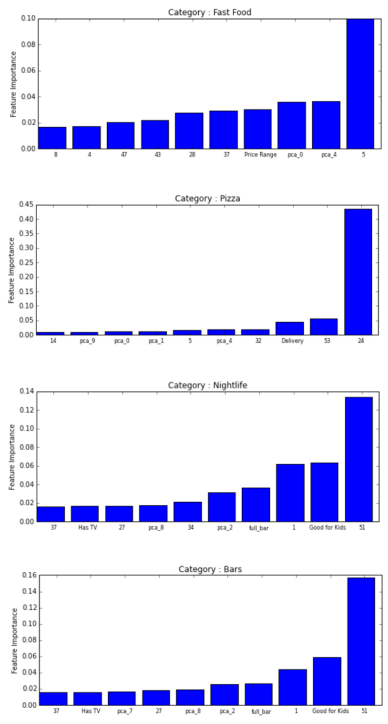
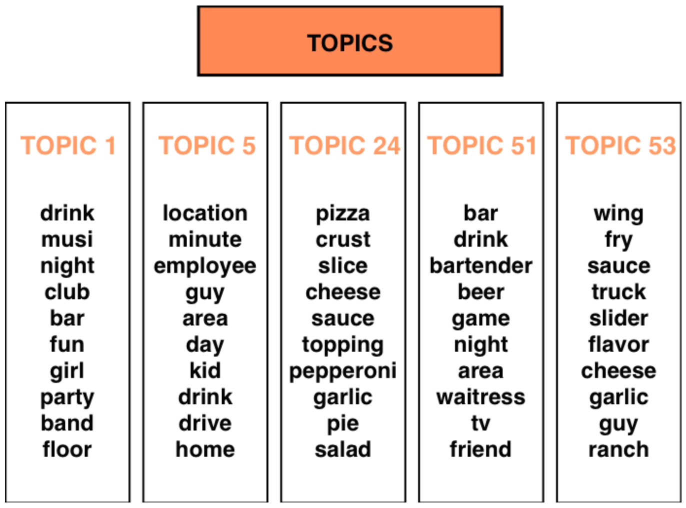


Figure 9: *Importance of the GS LDA features with PCA in the one-vs-all Random Forest classification*



TOPICS

TOPIC 1	TOPIC 5	TOPIC 24	TOPIC 51	TOPIC 53
drink	location	pizza	bar	wing
musi	minute	crust	drink	fry
night	employee	slice	bartender	sauce
club	guy	cheese	beer	truck
bar	area	sauce	game	slider
fun	day	topping	night	flavor
girl	kid	pepperoni	area	cheese
party	drink	garlic	waitress	garlic
band	drive	pie	tv	guy
floor	home	salad	friend	ranch

Figure 10: *Topics extracted from the Las Vegas reviews using GS*

First, considering the results for the OVI features, we observe that some properties provided by Yelp are discriminative for our classification. For example, the attribute *Good for Kids* helps to sort the Bars and the Nightlife categories which is not surprising. The Fast Food may be the restaurants with the largest number of reviews as they have the largest number of customers, the model confirms this with the high weight on the *reviews_count*. This is also a cheap restaurant, hence the importance of the price range. As a result, it is worth considering the features provided by Yelp as they help discriminate the entries.

Second, for the categories Pizza with the features extracted by the OVI we observe a discriminative feature which matchs the one about Pizza provided in the figure 3. Then, for the same LDA method, there is no discriminative feature for the other categories. Now, if we consider the results for the GS features, each category has a highly discriminative feature. Moreover, if we look at the most common words for each of these topics in the figure 10, we naturally understand their importance in the classification. This result confirms our analysis on the models. The Gibbs sampling method provides a finer topic distribution over the documents (here it is a labels distribution over the restaurants).

Lastly, it is worth noticing the effect of the PCA on the importance of the features. For both the OVI and the GS, if we consider the category pizza, the results with the PCA are much more clear-cut. The weight of the most important feature and its difference with those of the other features are higher. We can explain this because the projection gives more structure to the data and reduces the noise.

This part was about confronting our data to supervised methods to grasp their patterns and also coming up with a good classification. We provided empirical results to confirm the difference between the two most common LDA methods and proved that with the Gibbs sampling, the LDA can be really efficient to find the underlying topics of a set of documents, being much butter than a matrix factorization method. Related to our problem, it shows us that the features contain some information, but the LDA features remain more important to find the labels of a restaurant.

5. Unsupervised Clustering

5.1. Approach

For this part of the project, we use the same features as for the supervised classification approach, i.e. the topic assignments. We wanted to see if it was possible to retrieve the original classification only based on the reviews. To do so and in order to check if our classification attempt was successful, we sampled about 1000 restaurants having tags in the following list of 6 categories: Sushi, Steakhouse, Seafood, Mexican, Sports and Breakfast & Brunch. We then applied applied the following methodology.

Each restaurant is now represented as probability distribution over the latent topics. Using the Shannon distance (symmetric Kullback-Liebler Divergence), we created a distance matrix gathering information on how close 2 restaurants are based on their reviews. After many experimentations, we chose to transform this distance matrix into a weighted adjacency matrix:

- $w_{ij} = 5$ if $d_{Shannon}(r_i, r_j) < 1$,
- $w_{ij} = 0.1$ otherwise.

The choice of having a non-zero weight between two restaurants even though they are not "close" is motivated by the fact that many graph clustering algorithm and in particular the WalkTrap algorithm that we used and present next, will only work on a connected graph.

We then transformed this adjacency matrix in an unweighted graph and applied the Walktrap algorithm for community detection.

5.2. The WalkTrap Algorithm

The WalkTrap Algorithm is a community detection algorithm created by Pascal Pons and Matthieu Latapy [4]. The algortihm runs in time $O(n^2 \log n)$ and space $O(n^2)$ where n is the number of vertices in the graph. As mentioned in their paper, "the intuition behind the Walktrap is that random walks on a graph tend to get trapped into densely connected parts corresponding to communities".[4] It relies on a new metric used to evaluate the distance between two vertices in a graph:

$$r_{ij} = \sqrt{\sum_{k=1}^{n} \frac{(P^t_{ik} - P^t_{kj})^2}{d(k)}}$$

where P^t_{ik} is the transition probability in t steps and $d(k)$ is the degree of node k (number of edges incident to the vertex). We can then generalise this distance between two vertices to a distance between two communities. Using this distance, we can now apply a hierarchical clustering algorithm.

Algorithm 2 Walktrap Algorithm

```
1: Start with a partition $\mathcal{P}_1 = \{\{v\}, v \in V\}$
2: Compute the distances between all adjacent vertices
3: while $\mathcal{P}_t \neq V$ do
4:     Merge 2 communities $\mathcal{C}_i$ and $\mathcal{C}_j$ in $\mathcal{P}_k$ and create a new partition $\mathcal{P}_{k+1}$
5:     Evaluate the distances between the communities in this new partition
```

The choice of communities to merge in step 4 is made using Ward's method. We look at minimising the mean within-cluster variance:

$$\frac{1}{n_{\mathcal{C}}} \sum_{\mathcal{C} \in \mathcal{P}_k} \sum_{i \in \mathcal{C}} r^2_{i\mathcal{C}},$$

where $n_{\mathcal{C}}$ is the number of communities at iteration k, and $r_{i\mathcal{C}}$ is the distance from vertex i to its community $\mathcal{C}$.

5.3. Results

We ran the algorithm from the *igraph* package in R on the three graphs generated with the three approaches mentionned above (NMF, OVI LDA, GS LDA). The results where extremely similar. We outputted a dendogram (cf. Figure 3) representing the obtained clustering. We colored the tag of each business for a better readability. It is not yet entirely clear to us how to get the optimum number of clusters. We were puzzled to see that the Walktrap algorithm indicated that a cut into three big clusters represented the optimum partition. Knowing the structure of the sampled restaurants, we decided to further investigate the dendogram. As one can see on Figure 3, cutting the tree at different heights, we can obtain five clear colored communities, corresponding to five of the six tags we pre-selected.

We summarized this classification using a confusion matrix:

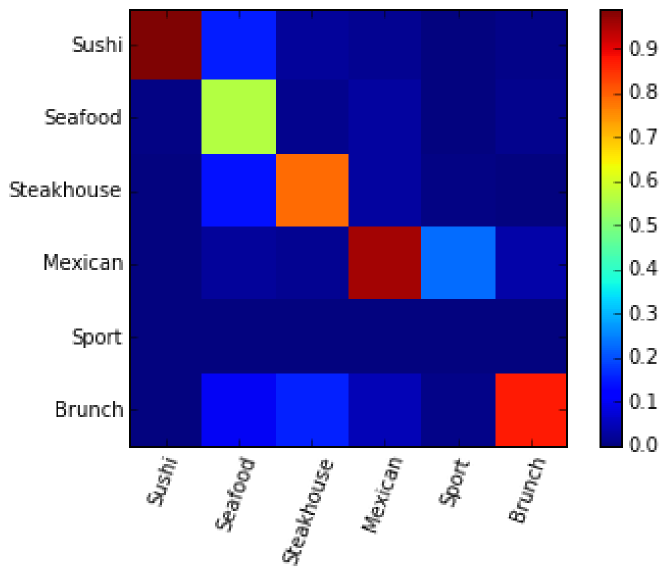


Figure 11: *Confusion Matrix using the Walktrap Algorithm*

With this method, we managed to detect 4 communities with great accuracy (over 80%). Nevertheless, this classification still has some flaws and the most obvious one is the misclassification or even non-classification of the Sports bars (yellow). We focused a bit more on these venues and explored manually the tags associated with them. We noticed that these Sports bar were most of the time having other tags such as "Restaurants","Bar", "American" and some even "Mexican". Reviews for these venues might have been misallocated due to the proximity of types of food, drinks or "ambiance" with Mexican restaurants. It is nonetheless interesting to note that were grouped almost all together inside the Mexican restaurants, and that if we cut the three at the sixth level then they would all be gathered in 2 cliques.

It seems that this method will succeed in making a difference between communities of restaurants if they are almost exlusive. It seems very unlikely to discover a restaurant that one can identify as both a Mexican and a Sushi place or even a Sushi place specialising in Breakfast (unless its speciality is the takagoyaki, a type of Japanese omelette made by "rolling together several layers of cooked egg"). It was often the case that misclassified restaurant had the tag "Buffet" which is for our purpose of classification our worst ennemy as it will phagocytose many categories at once.

6. Next steps

So far, we managed to extract the categories of the restaurants as latent features with a latent dirichlet allocation algorithm on the aggregated reviews for each restaurant.

Futur work could focus on the sub-cliques and try to get a finer classification by combining them with other features like check-ins, parking availability, etc. As a variant, we could also try a supervised LDA, where we use the existing categories as a response variable associated with each document and infer the joint model of the documents and the responses.

As a variant, we could try a supervised LDA, where we use the existing categories as a response variable associated with each document and infer the joint model of the documents and the responses. Lastly, this method is applicable on each review separately to predict the rating of the review, with a supervised lda also to avoid the predominance of the categories in the topics.

7. conclusion

By using a combination of unsupervised learning and graph theory, we managed to retrieve most of the original classification that is up to now still done by hand ! This work could result in an automation tool for Yelp to label properly its database.

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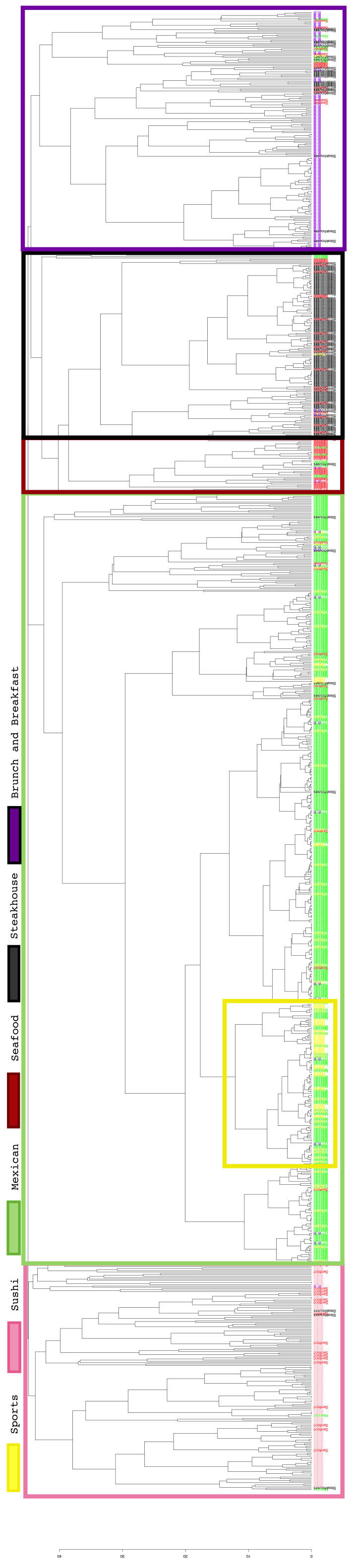

Figure 12: *Dendogram outputted by the Walktrap Algorithm*