

# Yelp Restaurant Tagging: A Multilabel Image Classification Problem

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# Data Description

Objective: predict tags of Yelp restaurants

Data set: 235k photos under 2000 restaurants



Randomly subset

Train set: 61k photos under 500 restaurants

Test set: 15k photos under 100 restaurants.

Sample photos:



# Labels and Models

## 9 Labels $\Rightarrow$ 9 Binary Classifiers

0: good_for_lunch	5: has_alcohol
1: good_for_dinner	6: has_table_service
2: takes_reservations	7: ambience_is_classy
3: outdoor_seating	8: good_for_kids
4: is_expensive	

## Models:

- Logistic regression
- SVM
- Convolutional Neural Network



# Label on Restaurant vs. Label on Image

Image level model: naively passing label

Restaurant level model: feature aggregation

# Label on Restaurant vs. Label on Image

Image level model: naively passing label





Restaurant level model: feature aggregation



Outdoor Seating ??

# Feature Extraction

Color feature

Texture feature: texture tile list = [    ...  ]

4,000

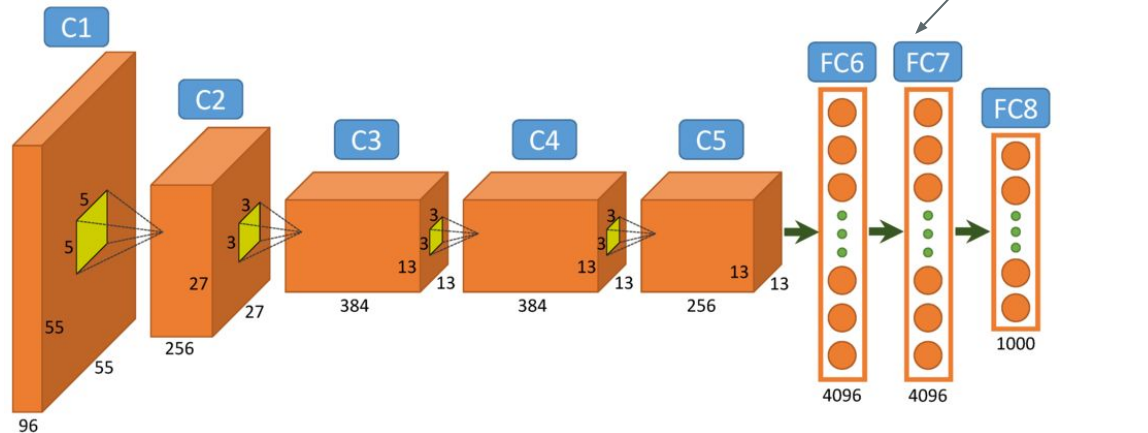
Deep learning feature

# Feature from Pre-trained model

Alexnet: trained on the ImageNet data

Training target: 10,000+ object categories

Features extracted: from the last hidden layer



# Image Level Model

Evaluation Metric: F1 score

Result aggregation:

1. Max: tag “good for lunch”  
and “outdoor seating”
2. Average : other tags

Image level model F1 score (aggregated)	
Color +Logistic	0.713
Texture +Logistic	0.684
Deep learning feature+Logistic	0.745
CNN	0.617

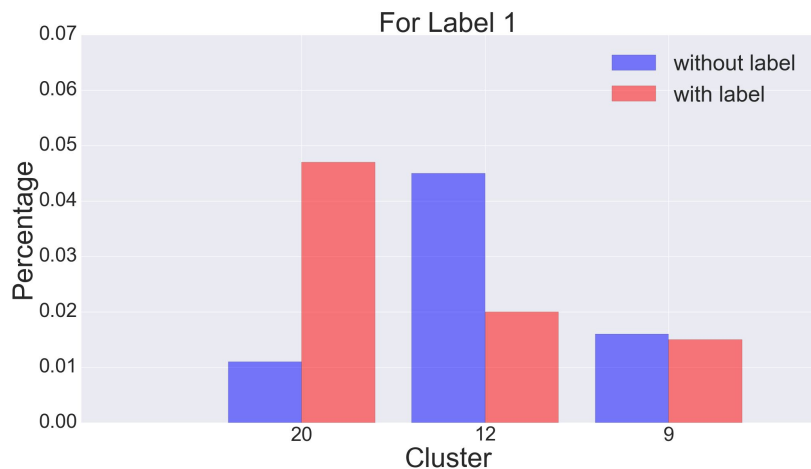
\*baseline score: 0.435



# Restaurant Level Model

K-means: 50 clusters of photos

Features: percentage of each cluster



Restaurant model F1 score	
Cluster using:	Logistic
Color	0.7252
Color +Texture	0.6361
Deep learning feature	0.7381

# CONCLUSION AND FUTURE WORK

Model	Best Scores
Image level	0.745
Restaurant level	0.738

\*Rank **top 25%** in Kaggle Leaderboard

## Future work:

1. Apply the best methods to the entire data set.
2. Fine tune pre-trained model

# Contact Information

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