An Experience with Text Classification in *Datadays 2019*

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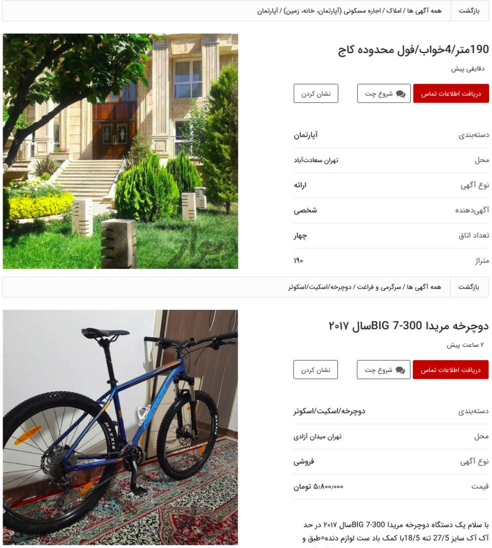
April, 2019

Divar Posts Dataset

- Released for DataDays 2019
- One million posts



Columns

- id
- archive_by_user
- published_at
- **cat1**
- **cat2**
- **cat3**
- city
- **title**
- **desc**
- price
- image_count
- platform
- mileage
- brand
- year
- type

The Problem: Categorization

- We need to categorize posts based on other posts features;
- We only use text features(title & description)!

Features

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No. of Classes

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Feature Extraction

Feature extraction is a dimensionality reduction process, where an initial set of raw variables is reduced to more manageable groups (features) for processing, while still accurately and completely describing the original data set.

Vectorizing the Text: Count Vectorizer

An example: We want to vectorize these 4 setences[1]:

1. Hello, how are you!
2. Win money, win from home.
3. Call me now
4. Hello, Call you tomorrow?

[1] Example from Rahul Vasaikar

Vectorizing the Text: Count Vectorizer

1. We first build a vocabulary:
   $vocabulary =$
   $\{are, call, from, hello, home, how, me, money, now, tomorrow, win, you\}$
2. Then, we vectorize each sentence based on the occurness of each word:

	are	call	from	hello	home	how	me	money	now	tom...	win	you
1	1	0	0	1	0	1	0	0	0	0	0	1
2	0	0	1	0	1	0	0	1	0	0	2	0
3	0	1	0	0	0	0	1	0	1	0	0	0
4	0	1	0	1	0	0	0	0	0	1	0	1

Vectorizing the Text: Count Vectorizer

N pair of samples

Tf-idf Vectoizer

- Tf-idf stands for term frequency-inverse document frequency
- a statistical measure used to evaluate how important a word is to a document in a collection or corpus
- the tf-idf weight is composed by two terms:

TF **Term Frequency**, which measures how frequently a term occurs in a document.

$$TF(t) = \frac{Number\ of\ times\ term\ t\ appears\ in\ a\ document}{Total\ number\ of\ terms\ in\ the\ document}$$

IDF **Inverse Document Frequency**, which measures how important a term is

$$IDF(t) = \ln \frac{Total\ number\ of\ documents}{Number\ of\ documents\ with\ term\ t\ in\ it}$$

Tf-idf Vectorizer: An Example

Consider a document containing 100 words wherein the word *cat* appears 3 times. The term frequency (i.e., tf) for cat is then $tf(cat) = \frac{3}{100} = 0.03$. Now, assume we have 10 million documents and the word cat appears in one thousand of these. Then, the inverse document frequency (i.e., idf) is calculated as $idf(cat) = \ln \frac{10{,}000{,}000}{1{,}000} = 4$. Thus, the Tf-idf weight is the product of these quantities: $tf - idf(cat) = 0.03 * 4 = 0.12$.

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Classification Algorithms

We used different classifiers and applied different models on the data. The classifiers we tested are:

- Naive Bayes
- Linear Support Vector Machine(SVM)
- Passive Aggressive
- Convolutional Neural Network(CNN)

Naive Bayes Classifier

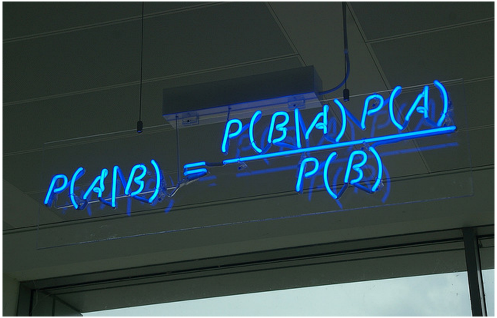


Photo by Matt Buck

Bayes Classifier: Naive One!

It is possible to show that accuracy is minimized, on average, by a very simple classifier that assigns each observation to the most likely class, given its predictor values. In other words, we should simply assign a test observation with predictor vector x_0 to the class j for which

$$P\left(Y = j \mid \mathbf{X} = \mathbf{x}\right)$$

is largest.

Bayes Classifier: Naive One!

We make two assumptions:

1. $X_1, X_2, \ldots, and\ X_m$ are independent from each other;
2. $X_1, X_2, \ldots, X_m \mid Y \sim MN(\cdot, p_1, p_2, \ldots, p_m)$

$$
\begin{aligned}
P(Y = j \mid \mathbf{X} = (x_1, x_2, \ldots, x_m)) &= \frac{P(\mathbf{X} = (x_1, x_2, \ldots, x_m) \mid Y = j) \cdot P(Y = j)}{P(\mathbf{X} = \mathbf{x})} \\
&= \frac{P(X_1 = x_1 \mid Y = j) \cdot \ldots \cdot P(X_m = x_m \mid Y = j) \cdot P(Y = j)}{P(\mathbf{X} = \mathbf{x})}.
\end{aligned}
$$

$$
\begin{aligned}
\hat{y} &= \underset{j \in classes}{\arg\max} \frac{P(X_1 = x_1 \mid Y = j) \cdot \ldots \cdot P(X_m = x_m \mid Y = j) \cdot P(Y = j)}{P(\mathbf{X} = \mathbf{x})} \\
&= \underset{j \in classes}{\arg\max} P(X_1 = x_1 \mid Y = j) \cdot \ldots \cdot P(X_m = x_m \mid Y = j) \cdot P(Y = j).
\end{aligned}
$$

Bayes Classifier: Naive One!

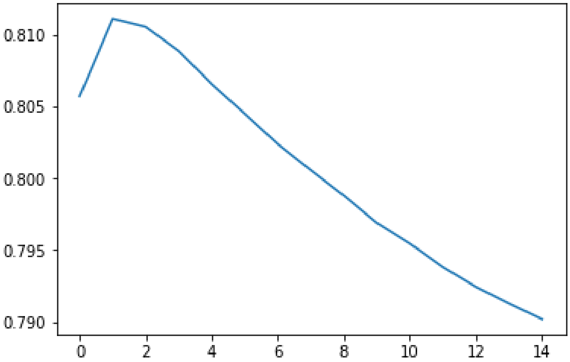
Let's dive into code!

Hyperparameters

Two important hyperparameters:

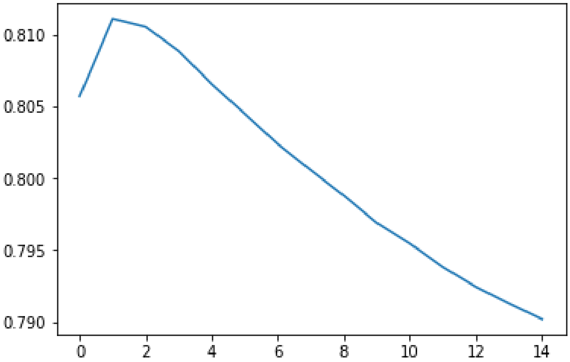
1. Size of the vocabulary;
2. Laplace/ Lidstone smoothing parameter(α).

Size of Vocabulary



It is convex! (to be completed)

Laplace/ Lidstone Smoothing Parameter(α)



It is convex! (to be completed)

Grid Search

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Linear SVM

- A non-probablistic classifier
- A discriminative classifier formally defined by a separating hyperplane
- The algorithm outputs an optimal hyperplane which categorizes new examples
- A good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class

Linear SVM: Behind the Scene

Given training vectors $x_i \in \mathbb{R}^p$, i=1,...,n, in two classes, and a vector $y \in \{1, -1\}^n$, SVM classifier solves the following primal problem:

$$\min_{w,b,\zeta} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \zeta_i$$
$$\text{subject to } y_i(w^T \phi(x_i) + b) \geq 1 - \zeta_i,$$
$$\zeta_i \geq 0, i = 1, ..., n$$

Its dual is:

$$\min_{\alpha} \frac{1}{2} \alpha^T Q \alpha - e^T \alpha$$
$$\text{subject to } y^T \alpha = 0$$
$$0 \leq \alpha_i \leq C, i = 1, ..., n$$

Linear SVM: Behind the Scene(cont'd)

where e is the vector of all ones, $C > 0$ is the upper bound, Q is an n by n positive semidefinite matrix, $Q_{ij} \equiv y_i y_j K(x_i, x_j)$, where $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ is the kernel. Here, training vectors are implicitly mapped into a higher (maybe infinite) dimensional space by the function ϕ. The decision function is:

$$\text{sgn}(\sum_{i=1}^{n} y_i \alpha_i K(x_i, x) + \rho)$$

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Thanks for your attention!

Codes in slides (in my GitHub):(github link)
Divar posts dataset:(divar link)
Any questions?