dm25s1

Topic 10 : Classification2

Part 02 : NaiveBayes

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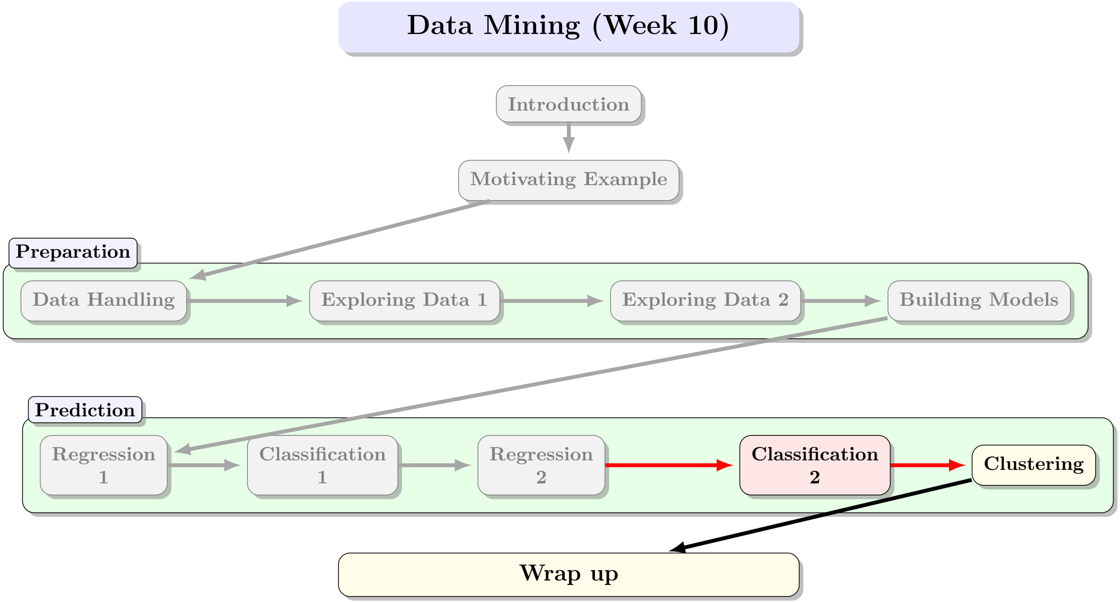
Outline

- Naive Bayes
- Ordinal Classification/Regression

Wrap up



Data Mining (Week 10)
Introduction
Motivating Example
Preparation
Data Handling
Exploring Data 1
Exploring Data 2
Building Models
Prediction
Regression 1
Classification 1
Regression 2
Classification 2
Clustering
Wrap up

Outline

Rev. Bayes and his theorem

Rev. Thomas Bayes, 1702–1761

Usage

Given $P(E|H)$ (Probability of Evidence (attributes) given the Hypothesis (the known classes) in the *training* set), Bayes theorem shows how to invert this relationship to get $P(H|E)$ (Probability of the Hypothesis (class) given the evidence (attributes) with an (unseen) *test case*).

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Bayes' Theorem

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (1)$$

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Application to classification

By convention, $A = H$ and $B = E$, where H is the hypothesis (observation has specific class) and E is the evidence form the training data in support of that hypothesis.

With this interpretation, the Bayes identity can be used to predict class probabilities (hypothesis) from features (evidence).

Conditional probabilities and Bayes terminology

Definition 1 (Conditional Probability)

If A and B are events, the Probability of A, given that B is true (has happened), written $P(A|B)$ is defined as follows:

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$P(A)$	Class prior; Prior probability
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- In data mining, B might represent the features (derived from the Data) for a given instance and A might represent the *predicted label* for these features.
- If A and B are independent events, $P(A \cap B) \equiv P(A)P(B)$, so $P(A|B) = P(A)$ and $P(B|A) = P(B)$.

Extended Naive Bayes

In practice, there could be multiple features/evidence so $B = \{B_1, B_2, \ldots, B_n\}$

.

Definition 2 (Extended Bayes Theorem)

The extended form, when $\{B_j\}$ partition B, so $B = \cup_j B_j$ and $B_p \cap B_q \equiv \emptyset$ unless $p = q$, is

$$P(A|\{B_i\}) = \frac{P(\{B_i\}|A)P(A)}{P(\{B_i\})} \tag{3}$$

which is the component-wise version of the standard Bayes Theorem.

Side note: Prosecutor's Fallacy

Note that $P(A|B) \neq P(B|A)$ in general. If the ratio $\frac{P(A)}{P(B)}$ is not close to 1, lawyers can mislead jurors regarding guilt or innocence. *Probability of Guilt given the evidence is not the same as the probability of the evidence assuming the defendant is guilty.* "Since the defendant is probably guilty, and we have proved he had the opportunity, he must have committed the crime."

Naive Extended Bayes

Definition 3 (Naive Bayes)

If the features B are assumed to be independent of each other, it can be shown that

$$P(B) = P(B_1 \cap B_2 \cap \ldots B_n) = \prod_i P(B_i) \tag{4}$$

$$P(B|A_j) = \prod_k P(B_i|A_j) \tag{5}$$

The naïve form of Bayes theorem becomes

$$P(A_j|B) = \frac{\prod_i P(B_i|A_j)P(A_j)}{\prod_i P(B_i)} \tag{6}$$

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- Bayes theorem provides the expression used to predict a new observation’s membership of each class (associated with a label).
- The observation is then assigned to the class for which its conditional probability is greatest.

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  - $P(B_i|A_j)$ (the evidence that the feature valued B_i predicts the class label A_j).
- From this, we can use the Naive version of the extended Bayes Theorem 6 to predict $P(A_j|B)$, the posterior probability of class label A_j given all the evidence from the features B.

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- When training Naïve Bayes, it is convenient to compute a table of *marginal counts*, as seen in the next slide, and to use these for prediction.

Fruit classification example

Example: Fruit classification

Type	Long	$\neg$Long	Sweet	$\neg$Sweet	Yellow	$\neg$Yellow	*Total*
Banana	400	100	350	150	450	50	*500*
Orange	0	300	150	150	300	0	*300*
Other	100	100	150	50	50	150	*200*
Total	*500*	*500*	*650*	*350*	*800*	*200*	*1000*

Source: stackoverflow

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Fruit classification : Precalculations

P(<Fruit>) = Total_<Fruit> / Total_* → P(Other) = 200/1000 = 0.2
P(<Feature>) = Total_<Feature> / Total_* → P(Sweet) = 650/1000 = 0.65
P(<Feature> | <Fruit>) = <Fruit,Feature> / Total_<Fruit> → P(Sweet | Other) = 150/200 = 0.75

Fruit classification example: prediction

Given observation: Long=L, Sweet=S, Yellow=Y fruit, what type of fruit is it?

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Banana - B

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$$= \frac{0.8 \times 0.7 \times 0.9 \times 0.5}{0.5 \times 0.65 \times 0.8}$$

$= 0.97$

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According to the MAP criterion, the observation (mystery fruit) is a banana!

Given the 3 binary-valued attributes, there are $2^3 = 8$ possible combinations - Naïve Bayes will classify each of these 8 combinations as one of the 3 fruit classes.

Naïve Bayes using scikit-learn

Setup

```python
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

Fit and Predict

```python
gnb = GaussianNB()
gnb.fit(Xtrain, ytrain)
y_gnbTest = gnb.predict(Xtest)
print(accuracy_score(ytest, y_gnbTest))
print(confusion_matrix(ytest, y_gnbTest))
print(classification_report(ytest, y_gnbTest, digits=3, target_names=target_names))
```

Note that `GaussianNB` rarely has arguments and numeric features do not need to be scaled before use

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- Categorical features are used to group counts of obaservations when computing probabilities
- But what about numerical features?
- Assume each numeric feature has a Gaussian distribution, characterised by its mean (μ) and standard deviation (σ) parameters
- `GaussianNB` fits this prior distribution to each numeric feature, when computing the marginal counts for the categorical features
- For a given test instance, its z-score for each numeric feature is computed from the fitted μ and σ for that feature (scaling is implicit).
- Hence, its likelihood for that probability distribution can be obtained, and substituted in the Naive Bayes (NB) expression over all the features, for each class value.
- The predicted class value is just the class value with the largest NB prediction over the features.

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- Implementations exist in `sklearn`: `from sklearn.naive_bayes import GaussianNB`, etc.

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➢ In the meantime, either Regression or Classification is used, with caveats…

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    - Support Vector Machines (SVM) were state of the art (1985-2000, say) and are still extremely effective for very high dimensional problems like document classification: a small number of support vectors define the decision boundary, so the classification decision collapses to 1D

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Classification is sometimes confused with clustering - will cover *clustering* next week.

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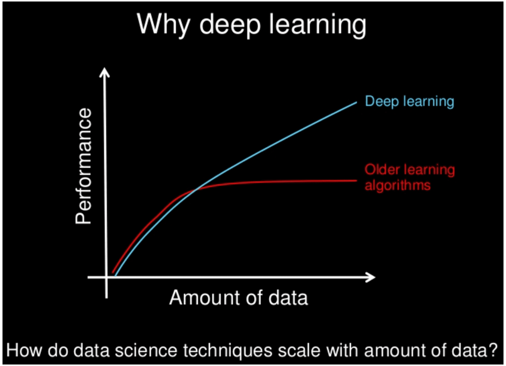

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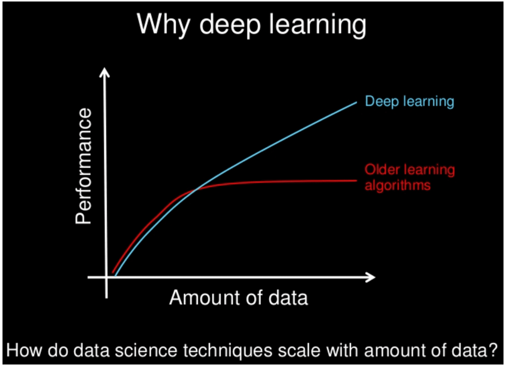

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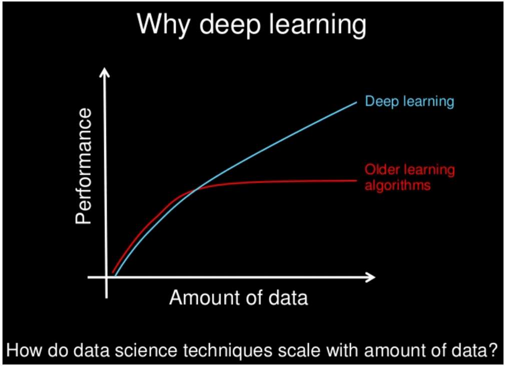

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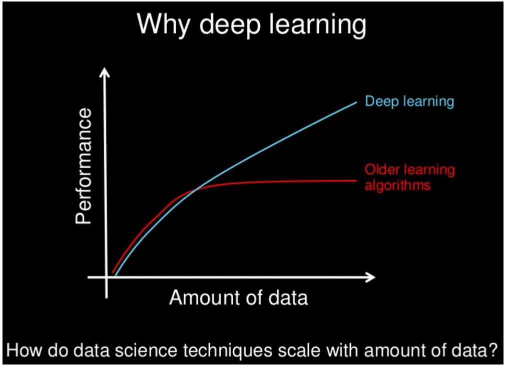

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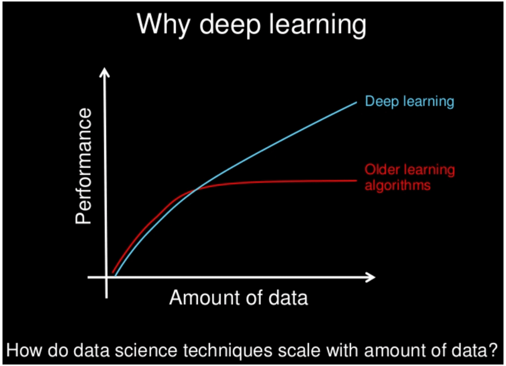

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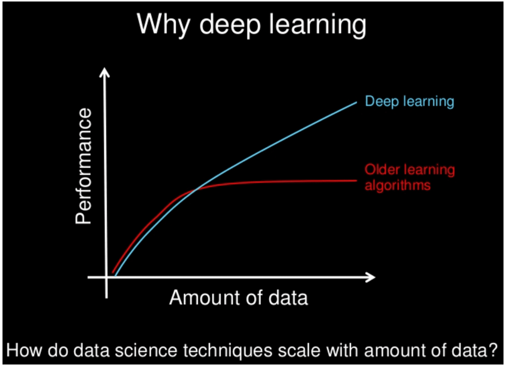

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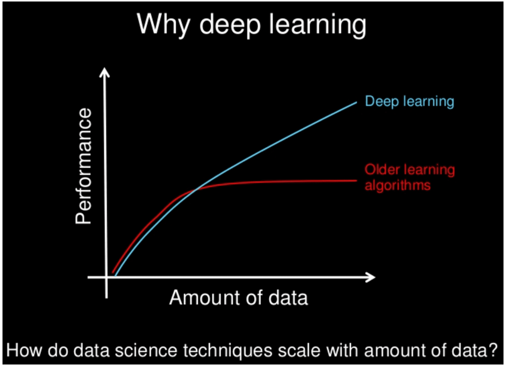

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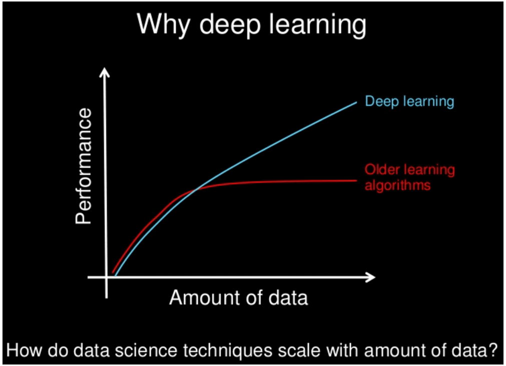

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Deep Learning will probably be covered in semester 2...

General References