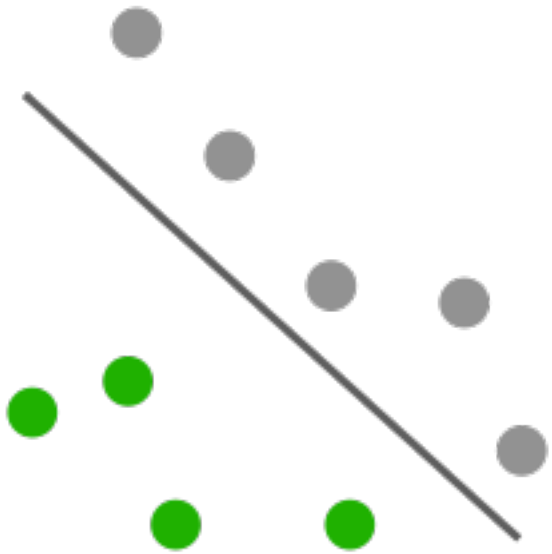
# Linear model



Examples:

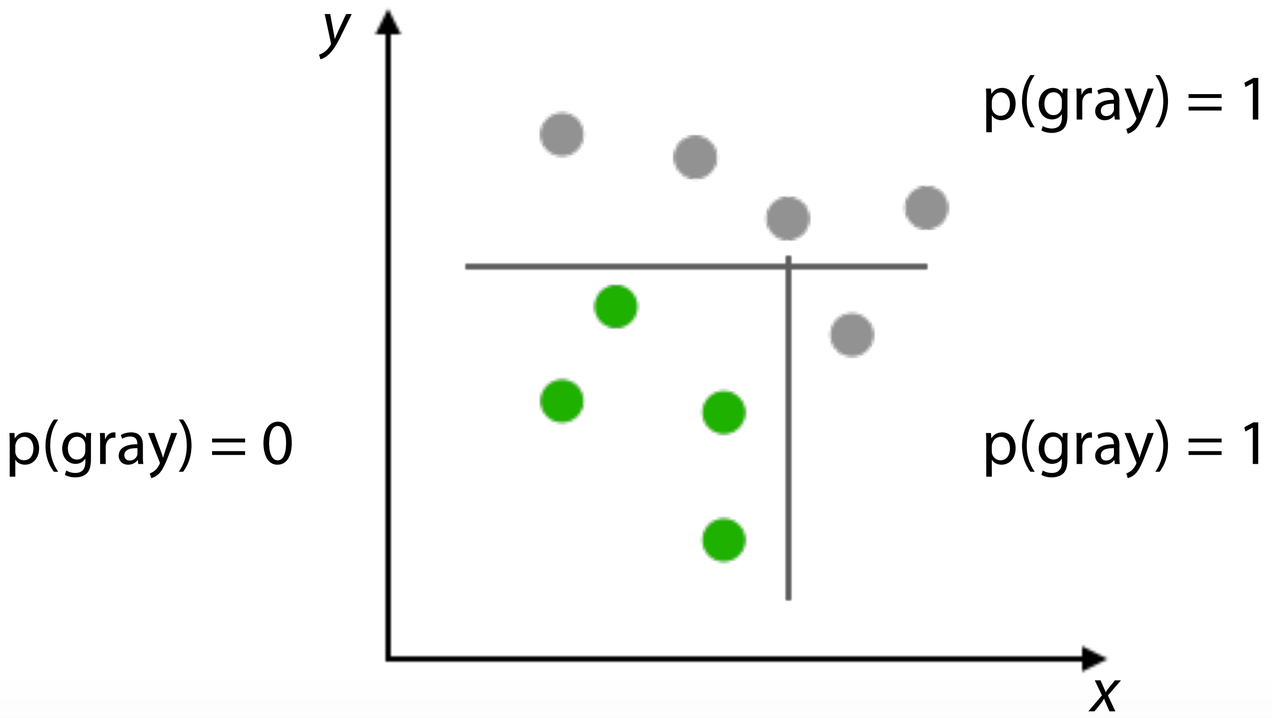
- Logistic Regression
- Support Vector Machines

# Linear model

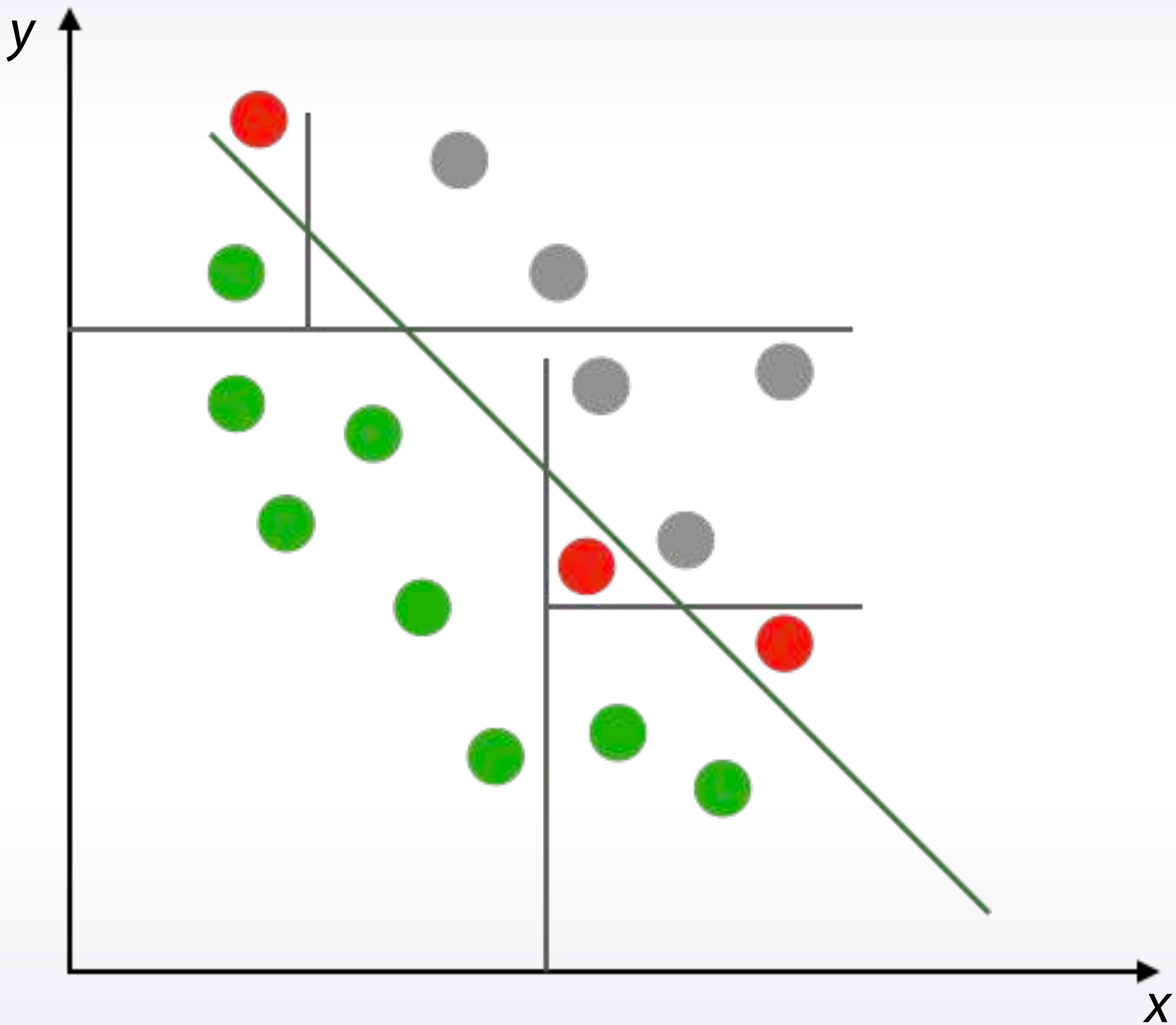
scikit learn

VOWPAL WABBIT

# Tree-based: Decision Tree, Random Forest, GBDT



# Tree-based: Decision Tree, Random Forest, GBDT



# Tree-based methods

scikit learn

dmlc XGBoost

Microsoft / LightGBM

# Conclusion

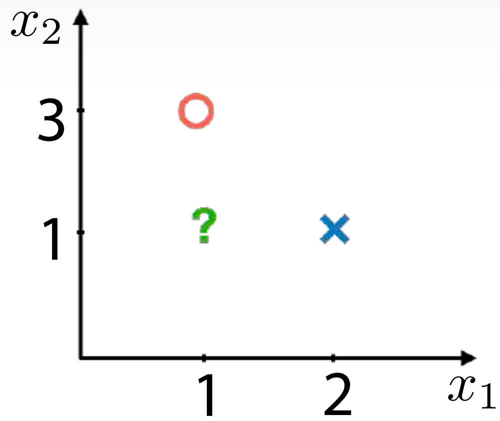
- There is no “silver bullet” algorithm
- Linear models  split space into 2 subspaces
- Tree-based methods splits space into boxes
- k-NN methods heavy rely on how to measure points “closeness”
- Feed-forward NNs produce smooth non-linear decision boundary

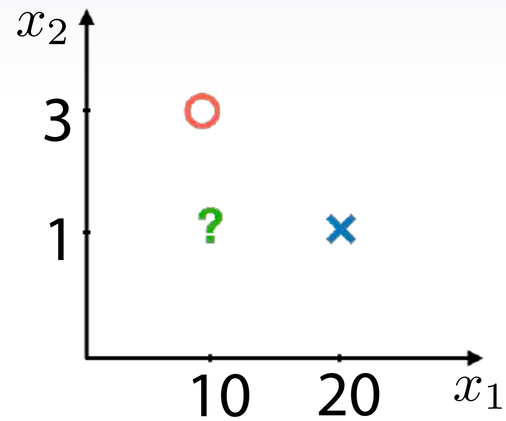
The most powerful methods are
**Gradient Boosted Decision Trees** and **Neural Networks**.
But you shouldn’t underestimate the others

# Numeric

- Preprocessing
  a) Tree-based models
  b) Non-tree-based models
- Feature generation

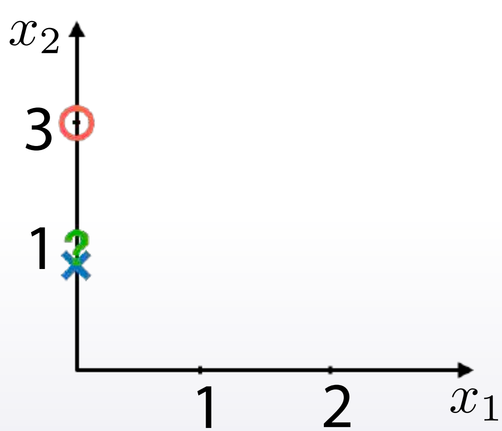
# Preprocessing: scaling

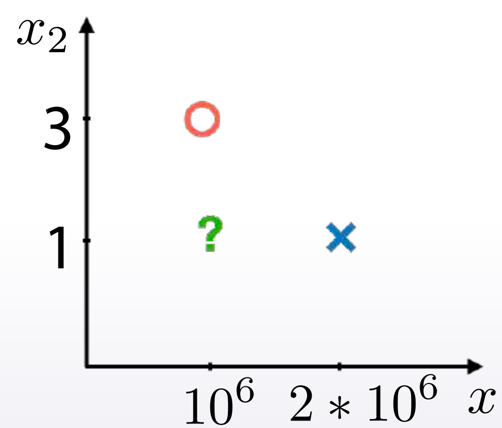



$$x_1 = x_1 * 0$$

$$x_1 = x_1 * 10^6$$



# Preprocessing: scaling

1. To [0,1]

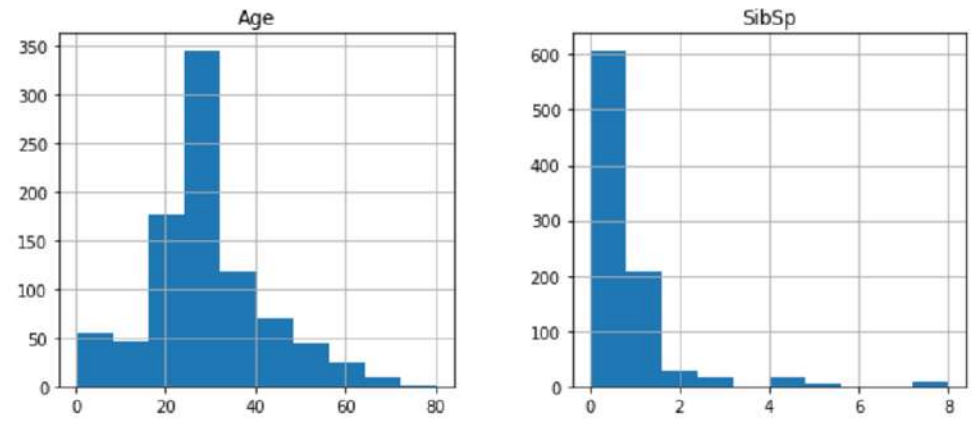
   `sklearn.preprocessing.MinMaxScaler`

$$X = (X - X.min())/(X.max() - X.min())$$

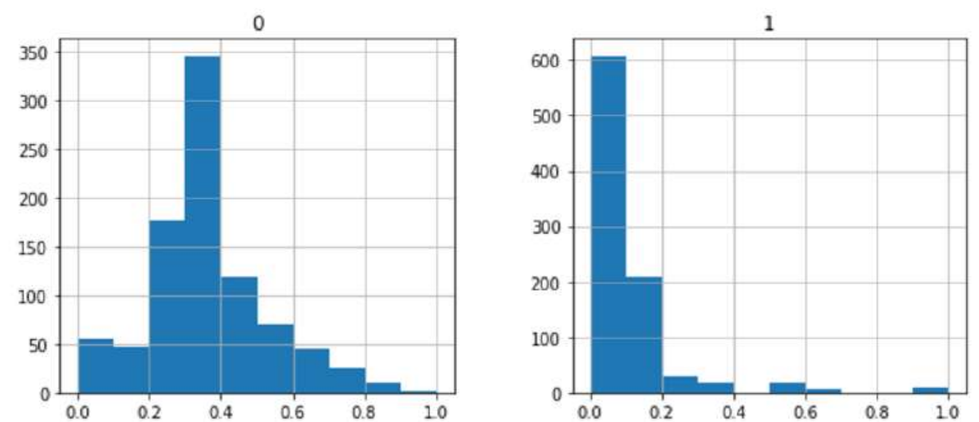
# Preprocessing: scaling

$$X = (X - X.min())/(X.max() - X.min())$$

```
train[['Age', 'SibSp']].hist(figsize=(10,4));
```




```
scaler = MinMaxScaler()
xtrain = scaler.fit_transform(train[['Age', 'SibSp']])
pd.DataFrame(xtrain).hist(figsize=(10,4));
```



# Preprocessing: scaling

1. To [0,1]

`sklearn.preprocessing.MinMaxScaler`

$$X = (X - X.min())/(X.max() - X.min())$$

2. To mean=0, std=1

`sklearn.preprocessing.StandardScaler`

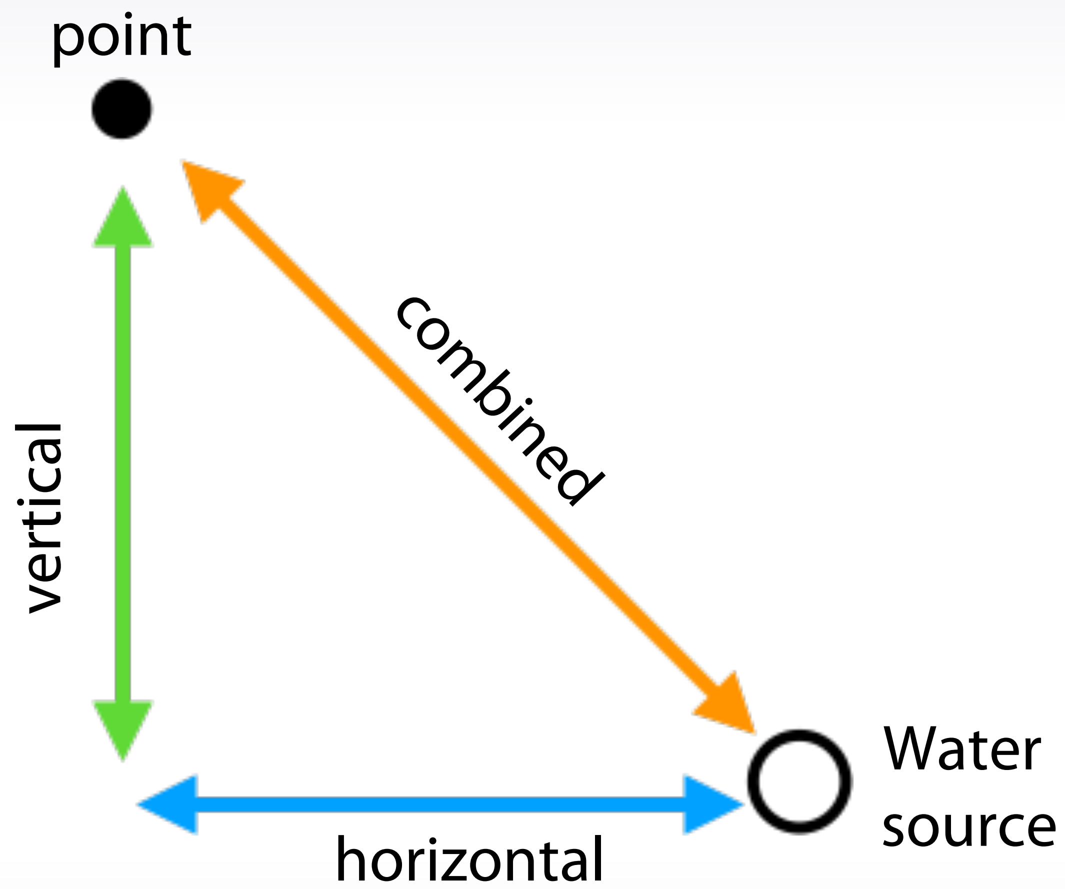
$$X = (X - X.mean())/X.std()$$

# Preprocessing: rank

- `rank([-100, 0, 1e5]) == [0,1,2]`
- `rank([1000,1,10]) = [2,0,1]`

`scipy.stats.rankdata`

# Feature generation




Combined = (horizontal ** 2 + vectical ** 2) ** 0.5

# Conclusion

1. Scaling and Rank for numeric features:
   a. Tree-based models doesn't depend on them
   b. Non-tree-based models hugely depend on them
2. Most often used preprocessings are:
   a. MinMaxScaler - to [0,1]
   b. StandardScaler - to mean==0, std==1
   c. Rank - sets spaces between sorted values to be equal
   d. np.log(1+x) and np.sqrt(1+x)
3. Feature generation is powered by:
   a. Prior knowledge
   b. Exploratory data analysis

# Categorical and ordinal features

# Categorical

## Titanic dataset

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare | Cabin | Embarked |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 0 | 3 | Braund, Mr. Owen Harris | male | 22.000000 | 1 | 0 | A/5 21171 | 7.2500 | NaN | S |
| 1 | 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th... | female | 38.000000 | 1 | 0 | PC 17599 | 71.2833 | C85 | C |
| 2 | 3 | 1 | 3 | Heikkinen, Miss. Laina | female | 26.000000 | 0 | 0 | STON/O2. 3101282 | 7.9250 | NaN | S |
| 3 | 4 | 1 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | female | 35.000000 | 1 | 0 | 113803 | 53.1000 | C123 | S |
| 4 | 5 | 0 | 3 | Allen, Mr. William Henry | male | 35.000000 | 0 | 0 | 373450 | 8.0500 | NaN | S |
| 5 | 6 | 0 | 3 | Moran, Mr. James | male | 29.699118 | 0 | 0 | 330877 | 8.4583 | NaN | Q |
| 6 | 7 | 0 | 1 | McCarthy, Mr. Timothy J | male | 54.000000 | 0 | 0 | 17463 | 51.8625 | E46 | S |
| 7 | 8 | 0 | 3 | Palsson, Master. Gosta Leonard | male | 2.000000 | 3 | 1 | 349909 | 21.0750 | NaN | S |

# Ordinal features

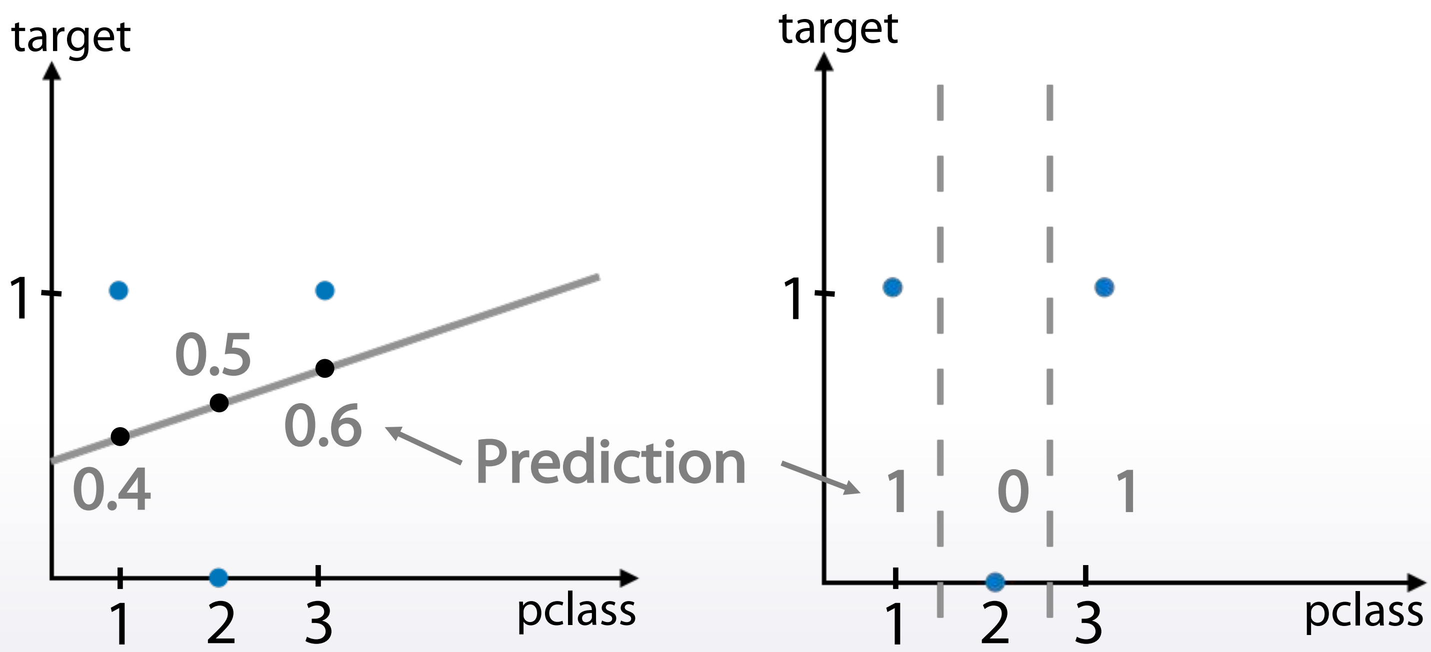
Ticket class: 1,2,3

Driver's license: A, B, C, D

Education: kindergarden, school, undergraduate, bachelor, master, doctoral

# Label encoding

| pclass | 1 | 2 | 3 |
|---|---|---|---|
| target | 1 | 0 | 1 |



# Label encoding

| K |
|---|
| embarked |
| S |
| C |
| S |
| S |
| S |
| Q |
| S |
| S |
| S |
| C |
| S |
| S |

1. Alphabetical (sorted)
   [S,C,Q] -> [2, 1, 3]

   `sklearn.preprocessing.LabelEncoder`

2. Order of appearance
   [S,C,Q] -> [1, 2, 3]

   `Pandas.factorize`

# Frequency encoding

| | K |
|---|---|
| | embarked |
| | S |
| | C |
| | S |
| | S |
| | S |
| | Q |
| | S |
| | S |
| | S |
| | C |
| | S |
| | S |

[S,C,Q] -> [0.5, 0.3, 0.2]

```
encoding = titanic.groupby('Embarked').size()
encoding = encoding/len(titanic)
titanic['enc'] = titanic.Embarked.map(encoding)
```

```
from scipy.stats import rankdata
```

# Categorical features

One-hot encoding

| pclass |
|---|
| 1 |
| 2 |
| 1 |
| 3 |

| pclass==1 | pclass==2 | pclass==3 |
|---|---|---|
| 1 | | |
| | 1 | |
| 1 | | |
| | | 1 |

`pandas.get_dummies, sklearn.preprocessing.OneHotEncoder`

# Categorical features

| pclass | sex | pclass_sex |
|---|---|---|
| 3 | male | 3male |
| 1 | female | 1female |
| 3 | female | 3female |
| 1 | female | 1female |

| Pclass_sex== | | | | | |
|---|---|---|---|---|---|
| 1male | 1female | 2male | 2female | 3male | 3female |
| | | | | 1 | |
| | 1 | | | | |
| | | | | | 1 |
| | 1 | | | | |

# Categorical features

1. Values in ordinal features are sorted in some meaningful order
2. Label encoding maps categories to numbers
3. Frequency encoding maps categories to their frequencies
4. Label and Frequency encodings are often used for tree-based models
5. One-hot encoding is often used for non-tree-based models
6. Interactions of categorical features can help linear models and KNN

# Datetime and coordinates

# Date and time

1. Periodicity
2. Time since
3. Difference between dates

# Date and time

1. Periodicity

Day number in week, month, season, year
second, minute, hour.

2. Time since
3. Difference between dates

# Date and time

1. Periodicity

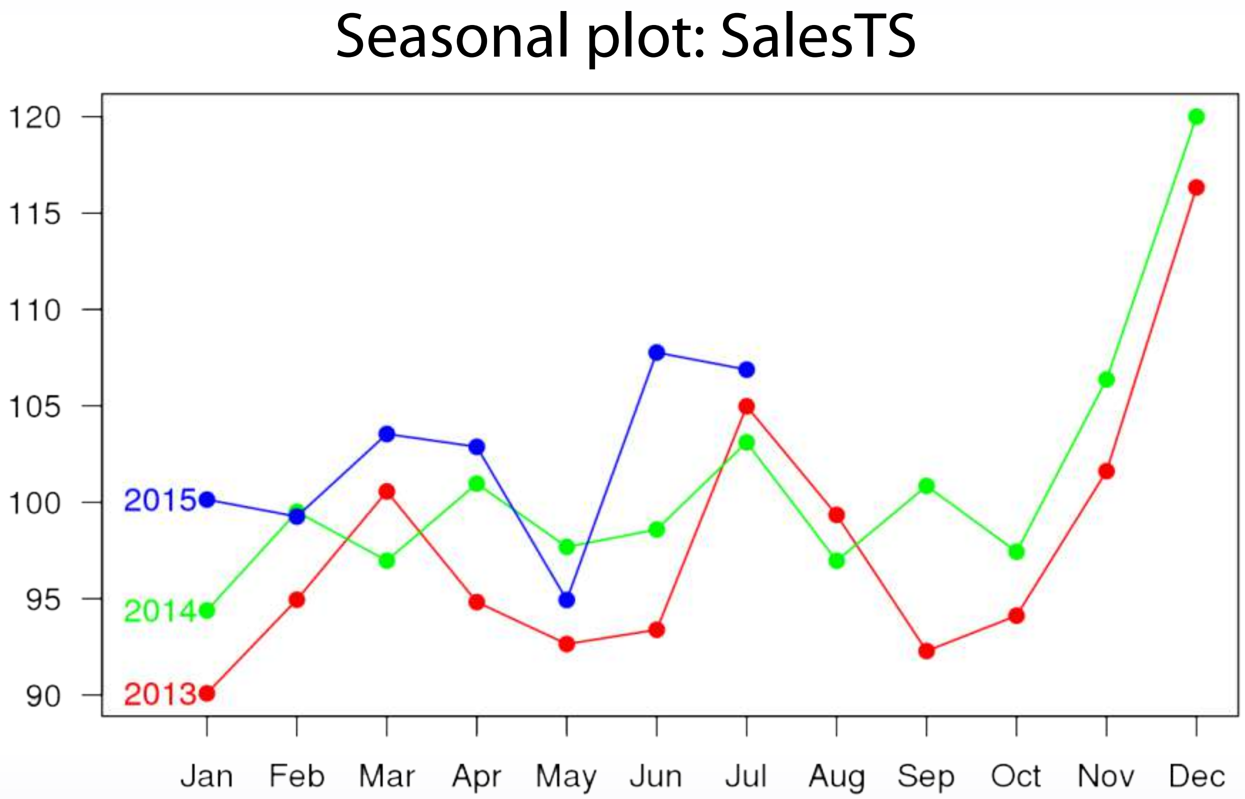
Day number in week, month, season, year
second, minute, hour.

2. Time since
   a. Row-independent moment
      For example: since 00:00:00 UTC, 1 January 1970;
   b. Row-dependent important moment
      Number of days left until next holidays/ time passed after last holiday.

3. Difference between dates

datetime_feature_1 - datetime_feature_2

# Date and time




Rossmann Store Sales, https://www.kaggle.com/thie1e/exploratory-analysis-rossmann

# Periodicity. «Time since»

| Date | weekday | daynumber_since_year_2014 | is_holiday | days_till_holidays | *sales* |
|---|---|---|---|---|---|
| 01.01.2014 | 5 | 0 | True | 0 | *1213* |
| 02.01.2014 | 6 | 1 | False | 3 | *938* |
| 03.01.2014 | 0 | 2 | False | 2 | *2448* |
| 04.01.2014 | 1 | 3 | False | 1 | *1744* |
| 05.01.2014 | 2 | 4 | True | 0 | *1732* |
| 06.01.2014 | 3 | 5 | False | 9 | *1022* |

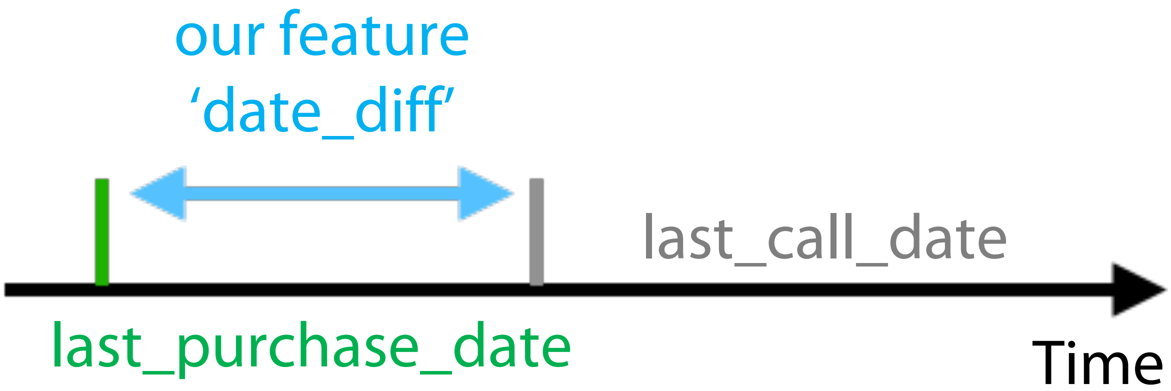
# Difference between dates

Churn prediction

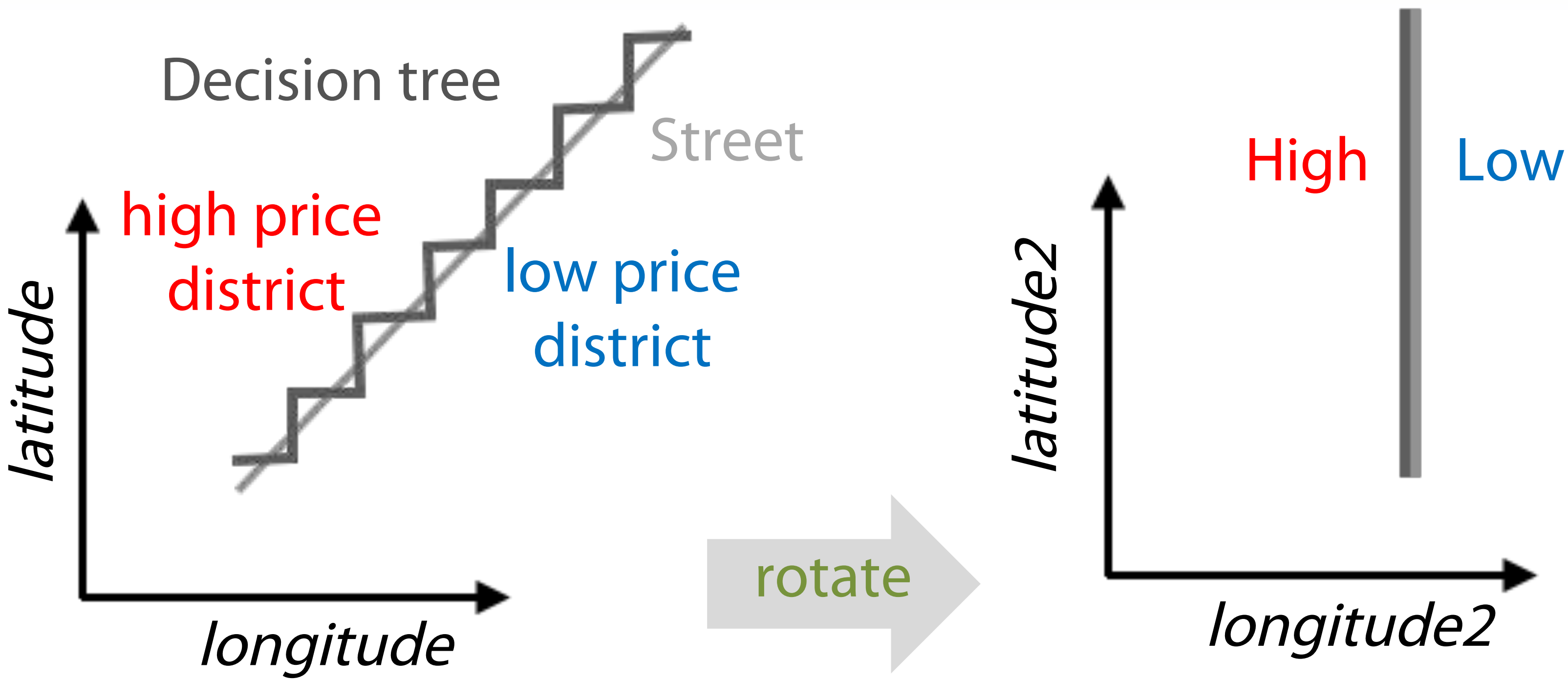
| user_id | registration_date | *last_purchase_date* | *last_call_date* | date_diff | churn |
|---|---|---|---|---|---|
| 14 | 10.02.2016 | 21.04.2016 | 26.04.2016 | 5 | 0 |
| 15 | 10.02.2016 | 03.06.2016 | 01.06.2016 | -2 | 1 |
| 16 | 11.02.2016 | 11.01.2017 | 11.01.2017 | 1 | 1 |
| 20 | 12.02.2016 | 06.11.2016 | 08.02.2017 | 94 | 0 |

# Difference between dates

For a particular user:



# Coordinates

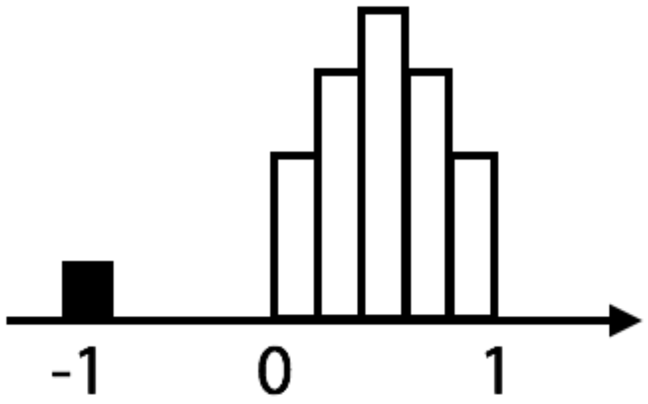


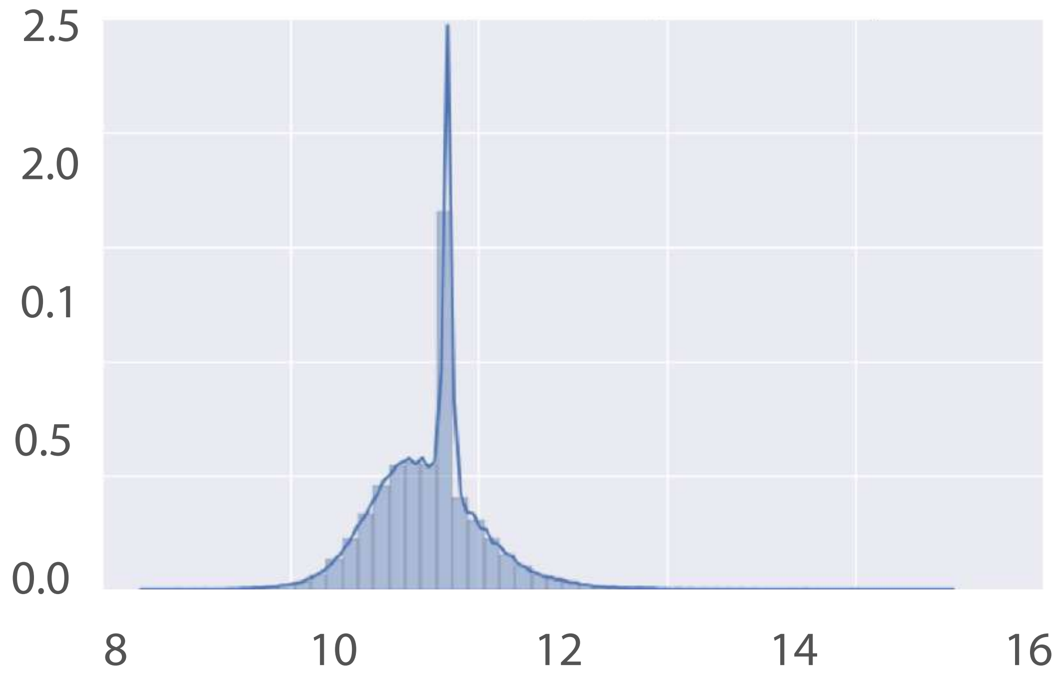
# Conclusion

1. Datetime
   a. Periodicity
   b. Time since row-independent/dependent event
   c. Difference between dates
2. Coordinates
   a. Interesting places from train/test data or additional data
   b. Centers of clusters
   c. Aggregated statistics

# Missing values

# Hidden NaNs



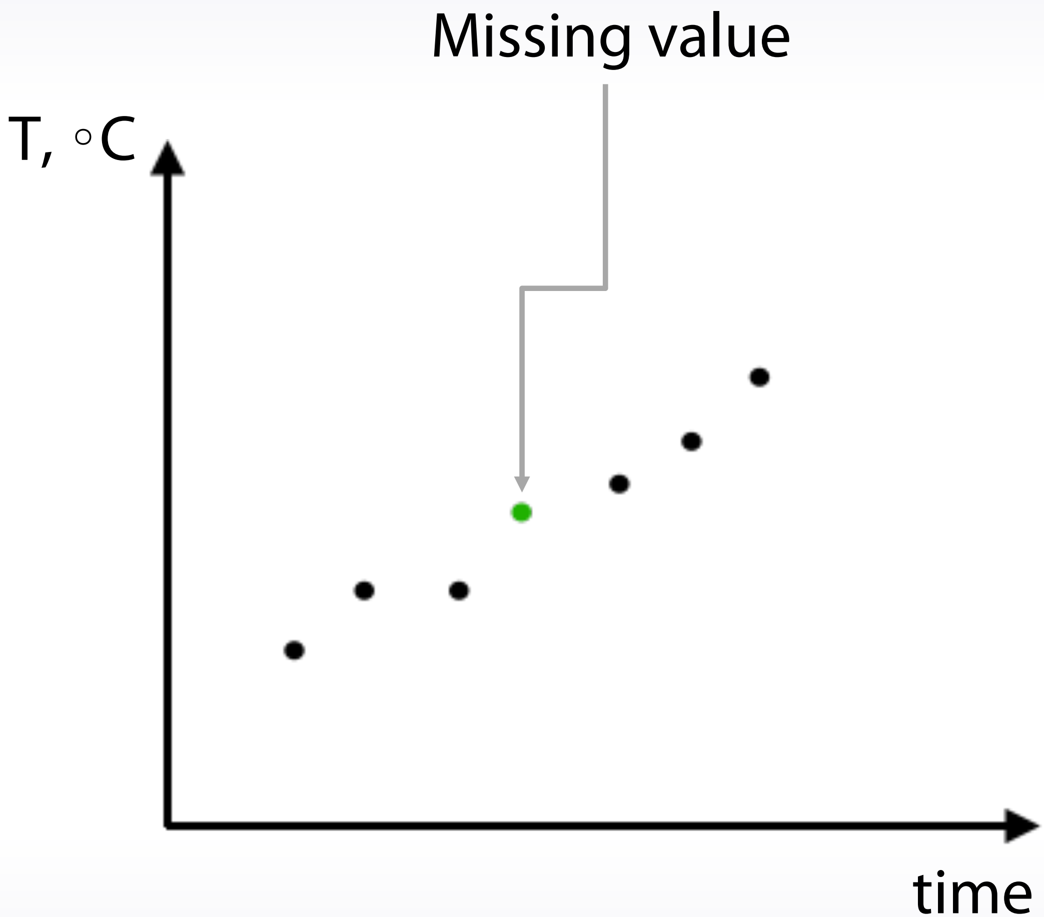
# Fillna approaches

1. -999, -1, etc
2. mean, median
3. Reconstruct value

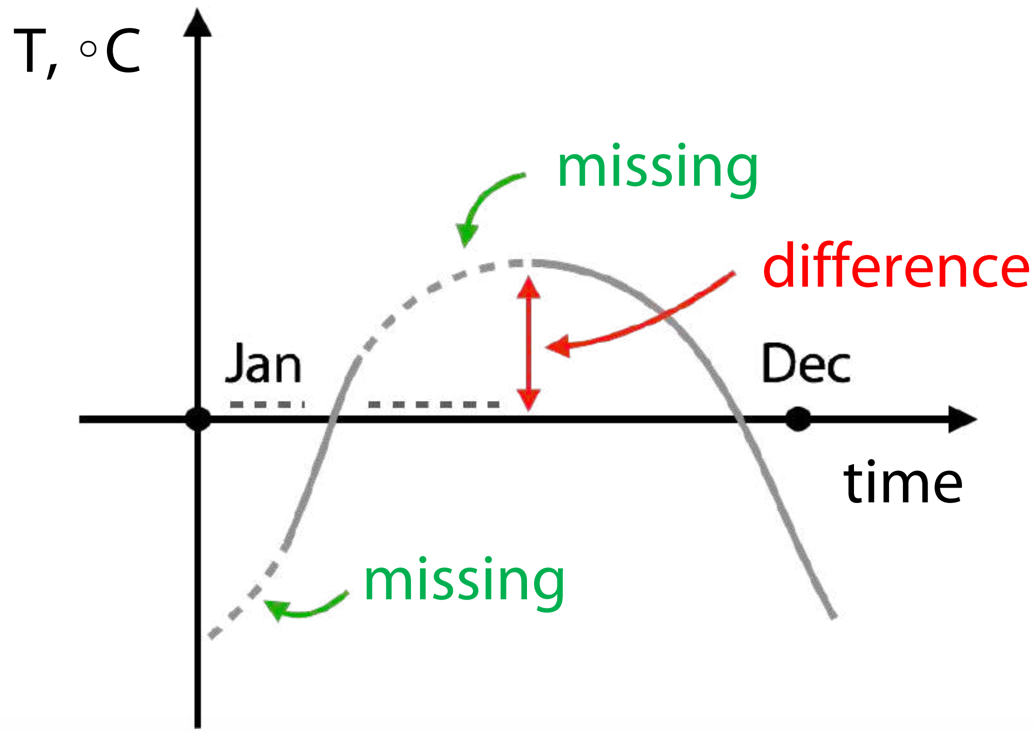
# “Isnull” feature

| feature | isnull |
|---|---|
| 0.1 | False |
| 0.95 | False |
| NaN | True |
| -3 | False |
| NaN | True |

# Missing values reconstruction



# Feature generation with missing values



# Feature generation with missing values

| categorical_ feature | numeric _feature |
|---|---|
| A | 1 |
| A | 4 |
| A | 2 |
| A | -1 |
| B | 9 |
| B | NaN |

# Feature generation with missing values

| categorical_ feature | numeric _feature | numeric_ feature_filled |
|---|---|---|
| A | 1 | 1 |
| A | 4 | 4 |
| A | 2 | 2 |
| A | -1 | -1 |
| B | 9 | 9 |
| B | NaN | -999 |

# Feature generation with missing values

| categorical_ feature | numeric _feature | numeric_ feature_filled | categorical _encoded |
|---|---|---|---|
| A | 1 | 1 | 1.5 |
| A | 4 | 4 | 1.5 |
| A | 2 | 2 | 1.5 |
| A | -1 | -1 | 1.5 |
| B | 9 | 9 | -495 |
| B | NaN | -999 | -495 |

# Treating values which do not present in train data

Train:

| categorical _feature | target |
|---|---|
| A | 0 |
| A | 1 |
| A | 1 |
| A | 1 |
| B | 0 |
| B | 0 |
| D | 1 |

Test:

| categorical _feature | target |
|---|---|
| A | ? |
| A | ? |
| B | ? |
| C | ? |

# Treating values which do not present in train data

Train:

| categorical_feature | categorical_encoded | target |
|---|---|---|
| A | 6 | 0 |
| A | 6 | 1 |
| A | 6 | 1 |
| A | 6 | 1 |
| B | 3 | 0 |
| B | 3 | 0 |
| D | 1 | 1 |

Test:

| categorical_feature | categorical_encoded | target |
|---|---|---|
| A | 6 | ? |
| A | 6 | ? |
| B | 3 | ? |
| C | 1 | ? |

# Treating values which do not present in train data

1. The choice of method to fill NaN depends on the situation
2. Usual way to deal with missing values is to replace them with -999, mean or median
3. Missing values already can be replaced with something by organizers
4. Binary feature “isnull” can be beneficial
5. In general, avoid filling nans before feature generation
6. Xgboost can handle NaN

# Feature extraction from texts and images

Common features + text

Titanic dataset

A1 | survived

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| 1 | survived | pclass | name | sex | age | sibsp |
| 2 | 0 | 3 | Braund, Mr. Owen Harris | male | 22 | 1 |
| 3 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Thayer) | female | 38 | 1 |
| 4 | 1 | 3 | Heikkinen, Miss. Laina | female | 26 | 0 |
| 5 | 1 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | female | 35 | 1 |
| 6 | 0 | 3 | Allen, Mr. William Henry | male | 35 | 0 |
| 7 | 0 | 3 | Moran, Mr. James | male | | 0 |
| 8 | 0 | 1 | McCarthy, Mr. Timothy J | male | 54 | 0 |
| 9 | 0 | 3 | Palsson, Master. Gosta Leonard | male | 2 | 3 |
| 10 | 1 | 3 | Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg) | female | 27 | 0 |
| 11 | 1 | 2 | Nasser, Mrs. Nicholas (Adele Achem) | female | 14 | 1 |
| 12 | 1 | 3 | Sandstrom, Miss. Marguerite Rut | female | 4 | 1 |
| 13 | 1 | 1 | Bonnell, Miss. Elizabeth | female | 58 | 0 |

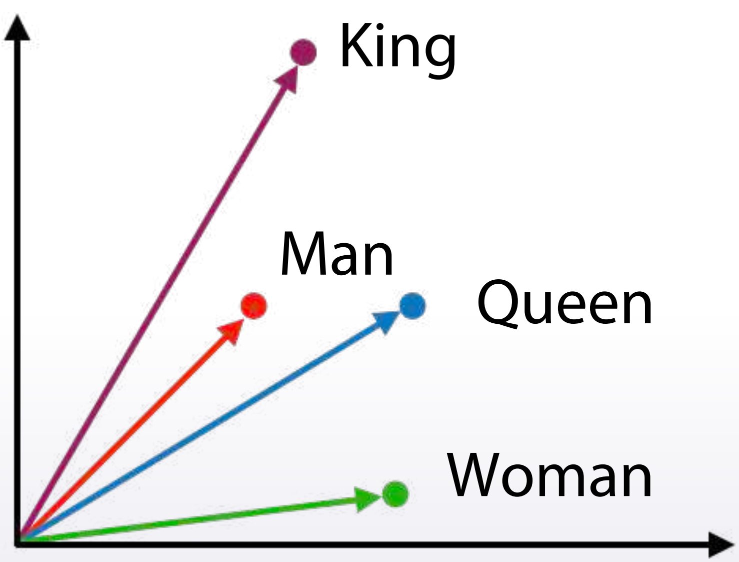
# Text -> vector

1. Bag of words:

The dog is on the table


2. Embeddings (~word2vec):

Word vectors



# Bag of words

| | | |
|---|---|---|
| (excited)<br>Hi everyone! | I'm so excited about this course! | So excited. SO EXCITED. EXCITED, I AM! |

CountVectorizer

| hi | every one | I'm | so | excited | about | this | course |
|---|---|---|---|---|---|---|---|
| 1 | 1 | | | 1 | | | |
| | | 1 | 1 | 1 | 1 | 1 | 1 |
| | | 1 | 2 | 3 | | | |

`sklearn.feature_extraction.text.CountVectorizer`

# Bag of words: TFiDF

**Term frequency**

tf = 1 / x.sum(axis=1) [:,None]

x = x * tf

**Inverse Document Frequency**

idf = np.log(x.shape[0] / (x > 0).sum(0))

x = x * idf

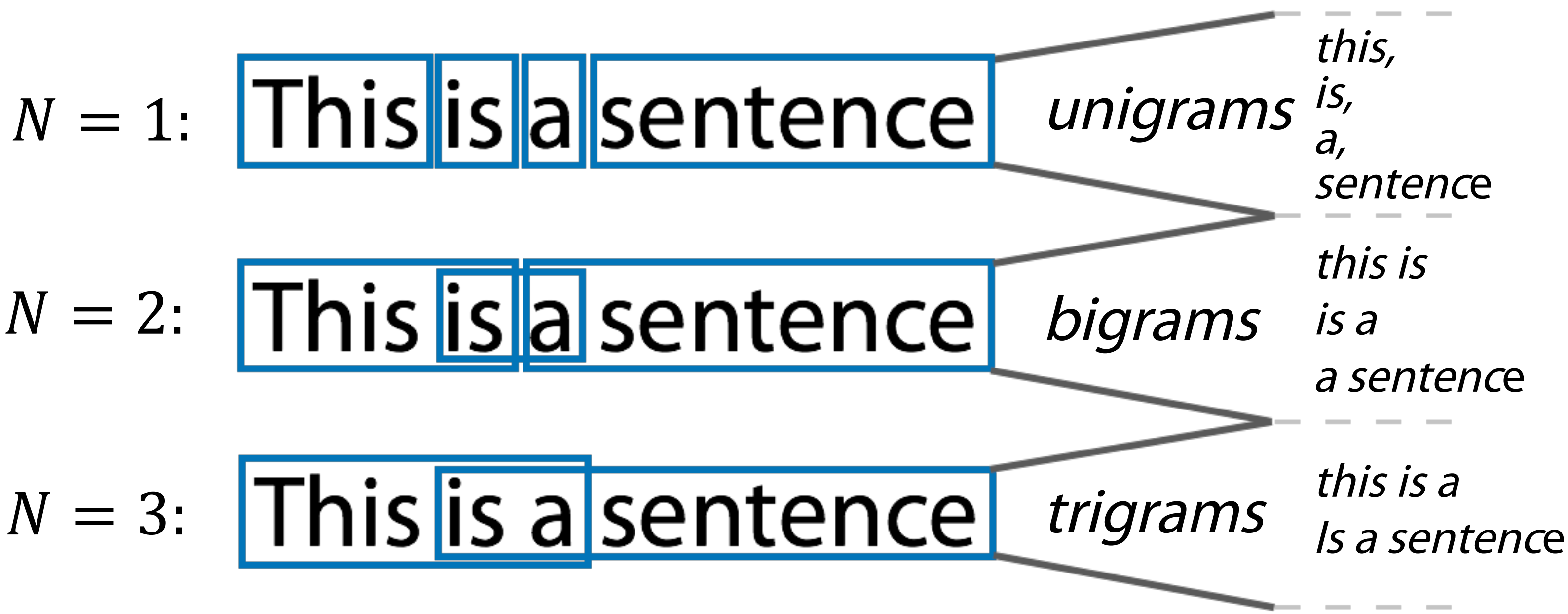
```
sklearn.feature_extraction.text.TfidfVectorizer
```

# Bag of words: TF+iDF

| | | |
|---|---|---|
| (excited)<br>Hi everyone! | I’m so excited about this course! | So excited. SO EXCITED. EXCITED, I AM! |

| hi | every one | I’m | so | excited | about | this | course |
|---|---|---|---|---|---|---|---|
| 0.36 | 0.36 | | | 0 | | | |
| | | 0.06 | 0.06 | 0 | 0.18 | 0.18 | 0.18 |
| | | 0.06 | 0.13 | 0 | | | |

# N-grams




`sklearn.feature_extraction.text.CountVectorizer:`
*`Ngram_range, analyzer`*

# Texts preprocessing

1. Lowercase
2. Lemmatization
3. Stemming
4. Stopwords

# Texts preprocessing: lowercase

| |
|---|
| Very, very sunny. |
| Sunny... Sunny! |

| Very | very | Sunny | sunny |
|---|---|---|---|
| 1 | 1 | 0 | 1 |
| 0 | 0 | 2 | 0 |

# Texts preprocessing: lemmatization and stemming

| | |
|---|---|
| I had a car | I have car |
| We have cars | We have car |

# Texts preprocessing: lemmatization and stemming

| | |
|---|---|
| I had a car | I have car |
| We have cars | We have car |

**Stemming:**

democracy, democratic, and democratization -> democr

Saw -> s

**Lemmatization**:

democracy, democratic, and democratization -> democracy

Saw -> see or saw (depending on context)

# Texts preprocessing: stopwords

Examples:

1. Articles or prepositions
2. Very common words

NLTK, Natural Language Toolkit library for python

```
sklearn.feature_extraction.text.CountVectorizer:
max_df
```

# Conclusion

Pipeline of applying BOW

1. Preprocessing:

   Lowercase, stemming, lemmatization, stopwords

2. Bag of words:

   Ngrams can help to use local context

3. Postprocessing: TFiDF

# Text -> vector

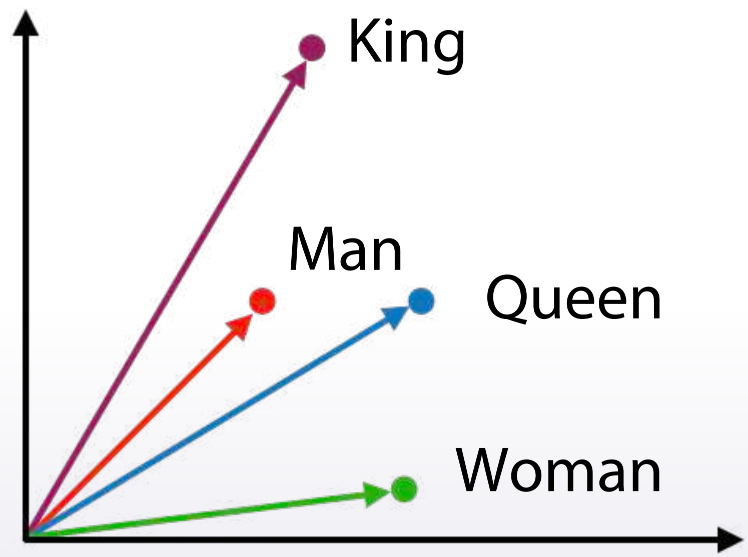
1. Bag of words:

The dog is on the table

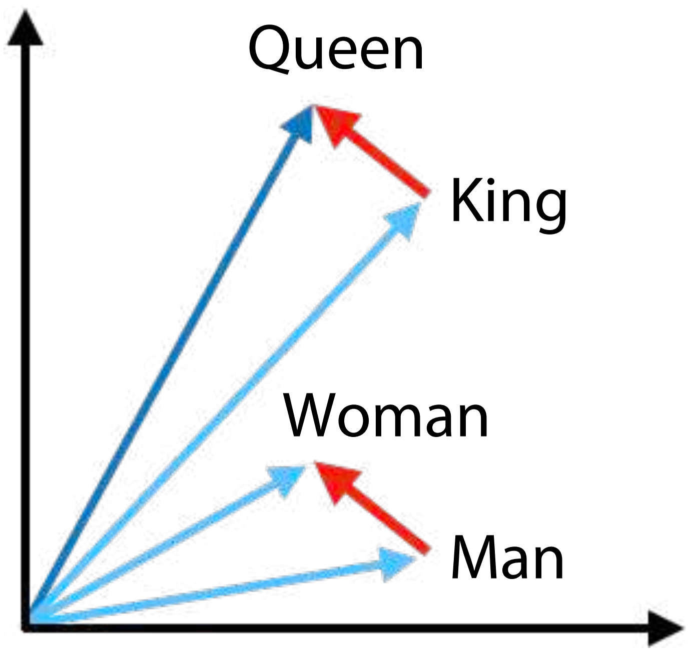
| 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 |
|---|---|---|---|---|---|---|---|
| are | cat | dog | is | now | on | table | the |

2. Embeddings (~word2vec):

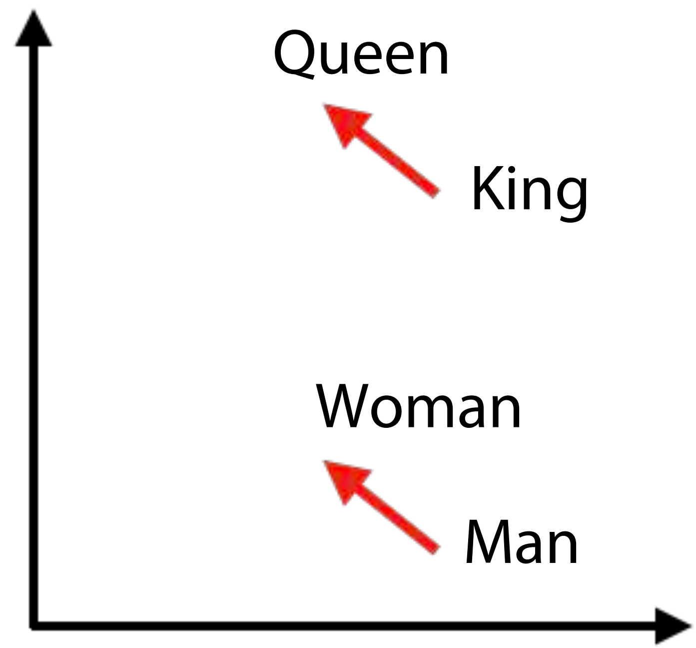
Word vectors



# Word2vec




king + woman - man = queen




The red direction encodes gender

# Word2vec

**Words:** Word2vec, Glove, FastText, etc

**Sentences:** Doc2vec, etc

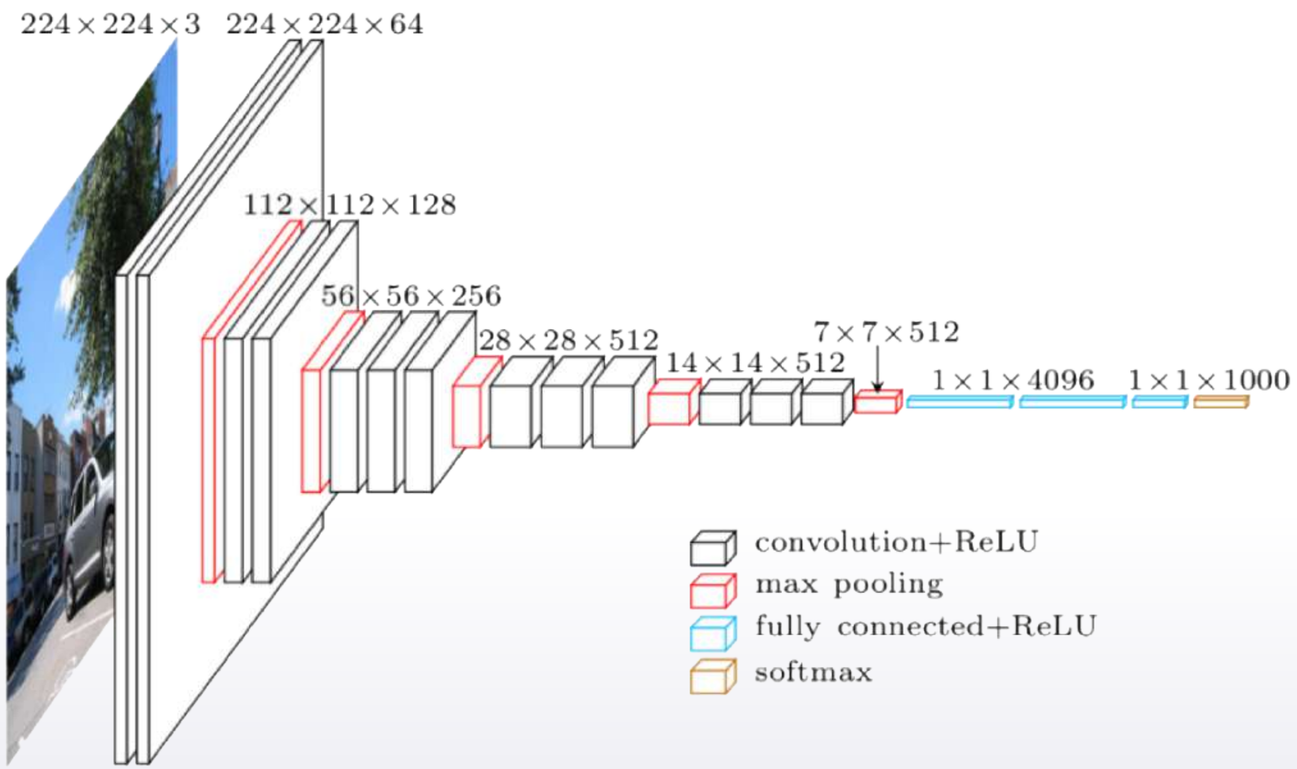
There are pretrained models

# BOW and w2v comparison

1. Bag of words
    a. Very large vectors
    b. Meaning of each value in vector is known
2. Word2vec
    a. Relatively small vectors
    b. Values in vector can be interpreted only in some cases
    c. The words with similar meaning often have similar embeddings

# Image -> vector

1. Descriptors
2. Train network from scratch
3. Finetuning



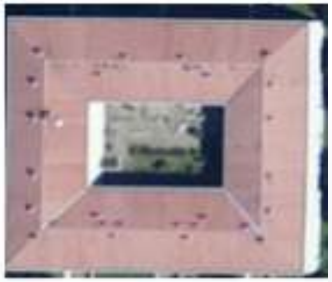
# Finetuning example

Category 1:
North-South orientation

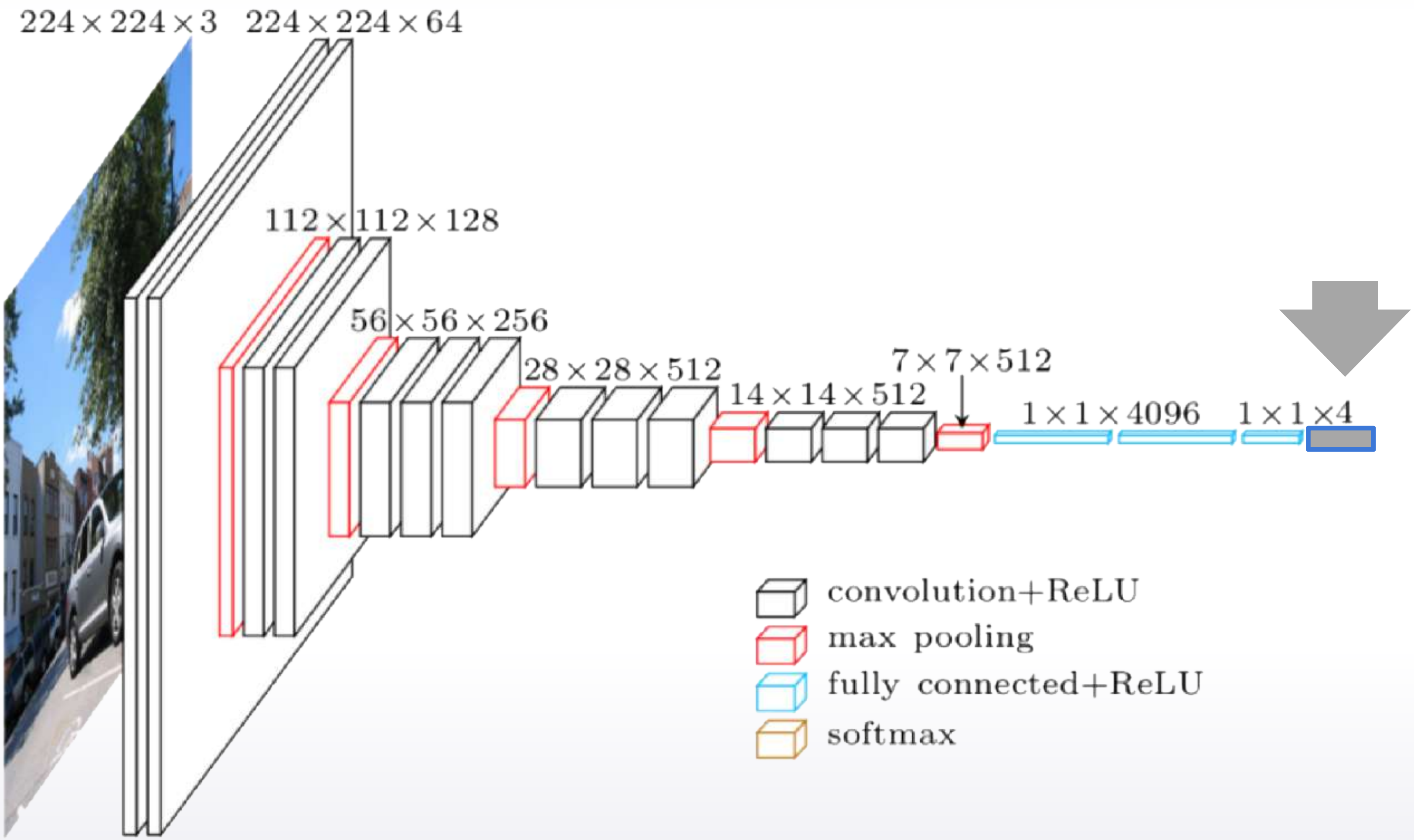
Category 3:
Flat roof

Category 2:
East-West orientation

Category 4:
Other



# Finetuning example



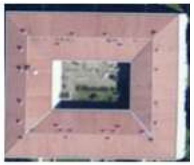
# Augmentation

Category 1:
North-South orientation

Category 3:
Flat roof

Category 2:
East-West orientation

Category 4:
Other



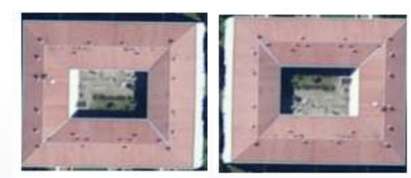
# Augmentation

## Category 1:
North-South orientation

## Category 2:
East-West orientation

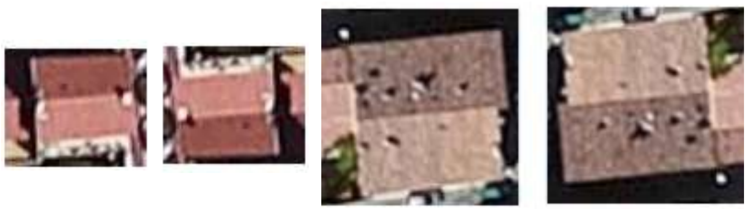
## Category 3:
Flat roof

## Category 4:
Other



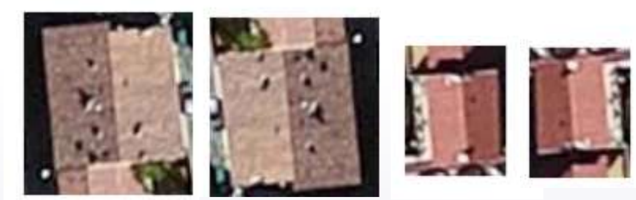
# Augmentation

Category 1:
North-South orientation

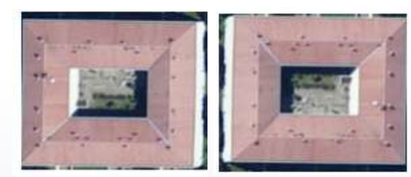


Category 3:
Flat roof

Category 2:
East-West orientation

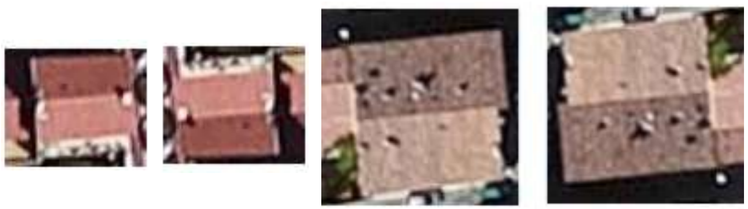


Category 4:
Other



# Augmentation

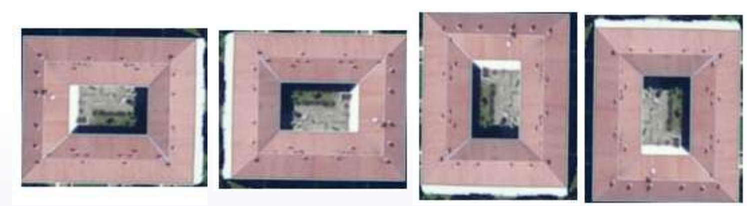
Category 1:
North-South orientation



Category 3:
Flat roof

Category 2:
East-West orientation

Category 4:
Other



# Feature extraction from text and images

1. **Texts**
   a. Preprocessing
      i. Lowercase, stemming, lemmarization, stopwords
   b. Bag of words
      i. Huge vectors
      ii. Ngrams can help to use local context
      iii. TFiDF can be of use as postprocessing
   c. Word2vec
      i. Relatively small vectors
      ii. Pretrained models
2. **Images**
   a. Features can be extracted from different layers
   b. Careful choosing of pretrained network can help
   c. Finetuning allows to refine pretrained models
   d. Data augmentation can improve the model