Introduction to preprocessing

PREPROCESSING FOR MACHINE LEARNING IN PYTHON

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What is data preprocessing?

- After exploratory data analysis and data cleaning
- Preparing data for modeling

- **Example:** transforming categorical features into numerical features (dummy variables)

Why preprocess?

- Transform dataset so it's suitable for modeling
- Improve model performance
- Generate more reliable results

Recap: exploring data with pandas

```
import pandas as pd
hiking = pd.read_json("hiking.json")
print(hiking.head())
```

```
  Prop_ID                    Name  ... lat lon
0    B057  Salt Marsh Nature Trail  ... NaN NaN
1    B073                Lullwater  ... NaN NaN
2    B073                  Midwood  ... NaN NaN
3    B073                Peninsula  ... NaN NaN
4    B073                Waterfall  ... NaN NaN
```

Recap: exploring data with pandas

```python
print(hiking.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 33 entries, 0 to 32
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
 --  ------          --------------  -----
 0   Prop_ID         33 non-null     object
 1   Name            33 non-null     object
 2   Location        33 non-null     object
 3   Park_Name       33 non-null     object
 4   Length          29 non-null     object
 5   Difficulty      27 non-null     object
 6   Other_Details   31 non-null     object
 7   Accessible      33 non-null     object
 8   Limited_Access  33 non-null     object
 9   lat             0 non-null      float64
 10  lon             0 non-null      float64
dtypes: float64(2), object(9)
memory usage: 3.0+ KB
```

Recap: exploring data with pandas

```
print(wine.describe())
```

```
             Type     Alcohol     ...   Alcalinity of ash
count  178.000000  178.000000     ...    178.000000
mean     1.938202   13.000618     ...     19.494944
std      0.775035    0.811827     ...      3.339564
min      1.000000   11.030000     ...     10.600000
25%      1.000000   12.362500     ...     17.200000
50%      2.000000   13.050000     ...     19.500000
75%      3.000000   13.677500     ...     21.500000
max      3.000000   14.830000     ...     30.000000
```

Removing missing data

```
print(df)
```

```
     A    B    C
0  1.0  NaN  2.0
1  4.0  7.0  3.0
2  7.0  NaN  NaN
3  NaN  7.0  NaN
4  5.0  9.0  7.0
```

```
print(df.dropna())
```

```
     A    B    C
1  4.0  7.0  3.0
4  5.0  9.0  7.0
```

Removing missing data

```
print(df)
```

```
     A    B    C
0  1.0  NaN  2.0
1  4.0  7.0  3.0
2  7.0  NaN  NaN
3  NaN  7.0  NaN
4  5.0  9.0  7.0
```

```
print(df.drop([1, 2, 3]))
```

```
     A    B    C
0  1.0  NaN  2.0
4  5.0  9.0  7.0
```

Removing missing data

```
print(df)
```

```
     A    B    C
0  1.0  NaN  2.0
1  4.0  7.0  3.0
2  7.0  NaN  NaN
3  NaN  7.0  NaN
4  5.0  9.0  7.0
```

```
print(df.drop("A", axis=1))
```

```
     B    C
0  NaN  2.0
1  7.0  3.0
2  NaN  NaN
3  7.0  NaN
4  9.0  7.0
```

Removing missing data

```
print(df)
```

```
     A    B    C
0  1.0  NaN  2.0
1  4.0  7.0  3.0
2  7.0  NaN  NaN
3  NaN  7.0  NaN
4  5.0  9.0  7.0
```

```
print(df.isna().sum())
```

```
A    1
B    2
C    2
dtype: int64
```

```
print(df.dropna(subset=["B"]))
```

```
     A    B    C
1  4.0  7.0  3.0
3  NaN  7.0  NaN
4  5.0  9.0  7.0
```

Removing missing data

```
print(df)
```

```
     A    B    C
0  1.0  NaN  2.0
1  4.0  7.0  3.0
2  7.0  NaN  NaN
3  NaN  7.0  NaN
4  5.0  9.0  7.0
```

```
print(df.dropna(thresh=2))
```

```
     A    B    C
0  1.0  NaN  2.0
1  4.0  7.0  3.0
4  5.0  9.0  7.0
```

Let's practice!

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Working With Data Types

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Why are types important?

```
print(volunteer.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 665 entries, 0 to 664
Data columns (total 35 columns):
 #   Column              Non-Null Count  Dtype
 --  ------              --------------  -----
 0   opportunity_id      665 non-null    int64
 1   content_id          665 non-null    int64
 2   vol_requests        665 non-null    int64
 3   event_time          665 non-null    int64
 4   title               665 non-null    object
 ..  ...                 ...             ...
 34  NTA                 0 non-null      float64
dtypes: float64(13), int64(8), object(14)
memory usage: 182.0+ KB
```

- `object` : string/mixed types
- `int64` : integer
- `float64` : float
- `datetime64` : dates and times

Converting column types

```
print(df)
```

```
   A        B    C
0  1   string  1.0
1  2  string2  2.0
2  3  string3  3.0
```

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3 entries, 0 to 2
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype
 --  ------  --------------  -----
 0   A       3 non-null      int64
 1   B       3 non-null      object
 2   C       3 non-null      object
dtypes: int64(1), object(2)
memory usage: 200.0+ bytes
```

Converting column types

```
print(df)
```

```
   A        B    C
0  1   string  1.0
1  2  string2  2.0
2  3  string3  3.0
```

```
df["C"] = df["C"].astype("float")
print(df.dtypes)
```

```
A      int64
B     object
C    float64
dtype: object
```

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Training and test sets

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Why split?

1. Reduces *overfitting*
2. Evaluate performance on a holdout set

Splitting up your dataset

```python
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
   X_train y_train
0      1.0       n
1      4.0       n
       ...
5      5.0       n
6      6.0       n

   X_test y_test
0     9.0      y
1     1.0      n
2     4.0      n
```

Stratified sampling

- Dataset of 100 samples: 80 **class 1** and 20 **class 2**
- Training set of 75 samples: 60 **class 1** and 15 **class 2**
- Test set of 25 samples: 20 **class 1** and 5 **class 2**

Stratified sampling

```
X_train,X_test,y_train,y_test = train_test_split(X, y, stratify=y, random_state=42)
```

```
y["labels"].value_counts()
```

```
class1    80
class2    20
Name: labels, dtype: int64
```

Stratified sampling

```
y_train["labels"].value_counts()
```

```
class1    60
class2    15
Name: labels, dtype: int64
```

```
y_test["labels"].value_counts()
```

```
class1    20
class2    5
Name: labels, dtype: int64
```

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Standardization

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What is standardization?

Standardization: transform *continuous* data to appear *normally distributed*

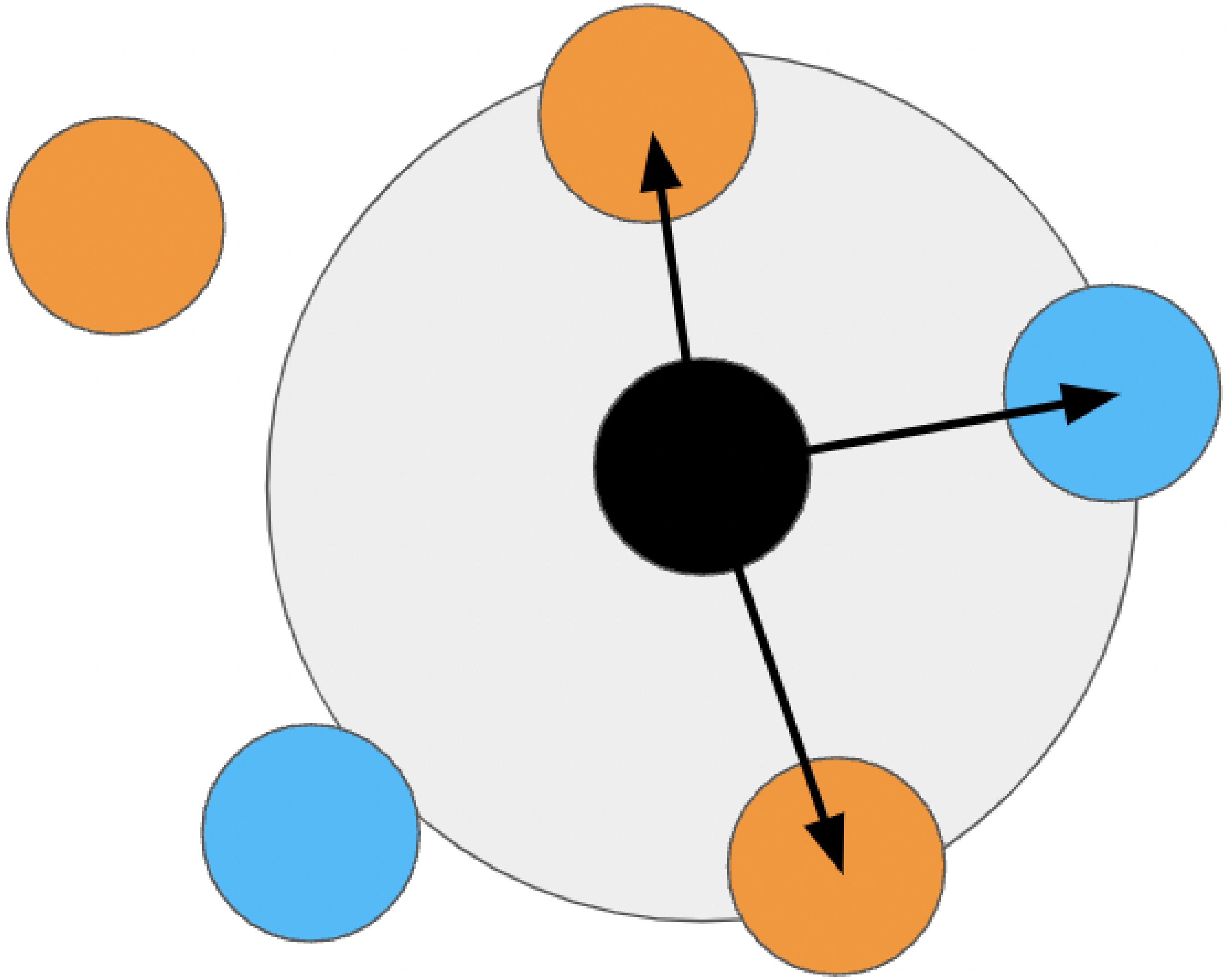
- `scikit-learn` models assume normally distributed data
- Using non-normal training data can introduce *bias*
- **Log normalization** and feature **scaling** in this course
- Applied to continuous numerical data

When to standardize: linear distances

- Model in *linear* space

Examples:

- k-Nearest Neighbors (kNN)
- Linear regression
- K-Means Clustering



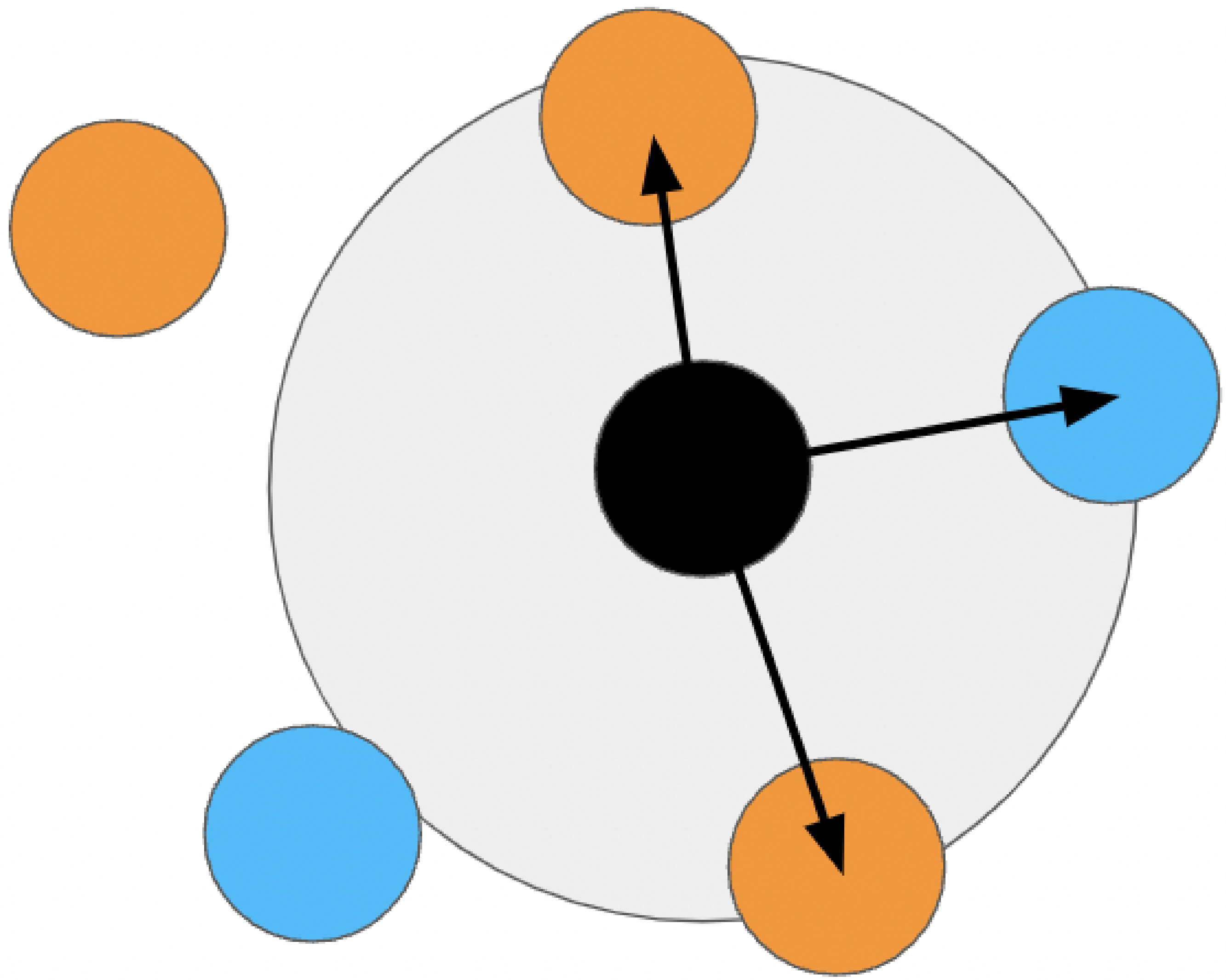
When to standardize: high variance

- Model in *linear* space

Examples:

- k-Nearest Neighbors (kNN)
- Linear regression
- K-Means Clustering

- Dataset features have *high variance*



When to standardize: different scales

- Features are on *different scales*

Example:

- Predicting house prices using *no. bedrooms* and *last sale price*

- Linearity assumptions

Let's practice!

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Log normalization

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What is log normalization?

- Useful for features with *high variance*
- Applies logarithm transformation
- Natural log using the constant e (≈ 2.718)

What is log normalization?

- Useful for features with *high variance*
- Applies logarithm transformation
- Natural log using the constant e (≈ 2.718)
- $e^{3.4} = 30$

- Captures relative changes, the magnitude of change, and keeps everything positive

Number	Log
30	3.4
300	5.7
3000	8

Log normalization in Python

```
print(df)
```

```
   col1   col2
0  1.00    3.0
1  1.20   45.5
2  0.75   28.0
3  1.60  100.0
```

```
print(df.var())
```

```
col1       0.128958
col2    1691.729167
dtype: float64
```

```
import numpy as np
df["log_2"] = np.log(df["col2"])
print(df)
```

```
   col1   col2     log_2
0  1.00    3.0  1.098612
1  1.20   45.5  3.817712
2  0.75   28.0  3.332205
3  1.60  100.0  4.605170
```

```
print(df[["col1", "log_2"]].var())
```

```
col1     0.128958
log_2    2.262886
dtype: float64
```

Let's practice!

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Scaling data

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What is feature scaling?

- Features on different scales
- Model with linear characteristics
- Center features around 0 and transform to variance of 1
- Transforms to approximately normal distribution

How to scale data

```
print(df)
```

```
   col1  col2   col3
0  1.00  48.0  100.0
1  1.20  45.5  101.3
2  0.75  46.2  103.5
3  1.60  50.0  104.0
```

```
print(df.var())
```

```
col1    0.128958
col2    4.055833
col3    3.526667
dtype: float64
```

How to scale data

```python
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df_scaled = pd.DataFrame(scaler.fit_transform(df),
                         columns=df.columns)
```

```python
print(df_scaled)
```

```
       col1      col2      col3
0 -0.442127  0.329683 -1.352726
1  0.200967 -1.103723 -0.553388
2 -1.245995 -0.702369  0.799338
3  1.487156  1.476409  1.106776
```

```python
print(df_scaled.var())
```

```
col1    1.333333
col2    1.333333
col3    1.333333
dtype: float64
```

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Standardized data and modeling

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K-nearest neighbors

- **Data leakage:** non-training data is used to train the model

```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, random_state=42)
knn = KNeighborsClassifier()
scaler = StandardScaler()

X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

knn.fit(X_train_scaled, y_train)
knn.score(X_test_scaled, y_test)
```

Let's practice!

Feature engineering

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What is feature engineering?

Feature engineering: Creation of new features from existing ones

- Improve performance
- Insight into relationships between features
- Need to understand the data first!
- Highly dataset-dependent

Feature engineering scenarios

Id	Text
1	"Feature engineering is fun!"
2	"Feature engineering is a lot of work."
3	"I don't mind feature engineering."

user	fav_color
1	blue
2	green
3	orange

Feature engineering scenarios

Id	Date
4	July 30 2011
5	January 29 2011
6	February 05 2011

user	test1	test2	test3
1	90.5	89.6	91.4
2	65.5	70.6	67.3
3	78.1	80.7	81.8

Let's practice!

Encoding categorical variables

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Categorical variables

```
   user subscribed fav_color
0     1          y      blue
1     2          n     green
2     3          n    orange
3     4          y     green
```

Encoding binary variables - pandas

```
print(users["subscribed"])
```

```
0    y
1    n
2    n
3    y
Name: subscribed, dtype: object
```

```
print(users[["subscribed", "sub_enc"]])
```

```
  subscribed  sub_enc
0          y        1
1          n        0
2          n        0
3          y        1
```

```
users["sub_enc"] = users["subscribed"].apply(lambda val: 1 if val == "y" else 0)
```

Encoding binary variables - scikit-learn

```python
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
users["sub_enc_le"] = le.fit_transform(users["subscribed"])

print(users[["subscribed", "sub_enc_le"]])
```

```
  subscribed  sub_enc_le
0          y           1
1          n           0
2          n           0
3          y           1
```

One-hot encoding

fav_color
blue
green
orange
green

Values: [blue, green, orange]

- blue: [1, 0, 0]
- green: [0, 1, 0]
- orange: [0, 0, 1]

fav_color_enc
[1, 0, 0]
[0, 1, 0]
[0, 0, 1]
[0, 1, 0]

```
print(users["fav_color"])
```

```
0      blue
1     green
2    orange
3     green
Name: fav_color, dtype: object
```

```
print(pd.get_dummies(users["fav_color"]))
```

```
   blue  green  orange
0     1      0       0
1     0      1       0
2     0      0       1
3     0      1       0
```

Let's practice!

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Engineering numerical features

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```python
print(temps)
```

```
     city  day1  day2  day3
0     NYC  68.3  67.9  67.8
1      SF  75.1  75.5  74.9
2      LA  80.3  84.0  81.3
3  Boston  63.0  61.0  61.2
```

```python
temps["mean"] = temps.loc[:,"day1":"day3"].mean(axis=1)
print(temps)
```

```
     city  day1  day2  day3   mean
0     NYC  68.3  67.9  67.8  68.00
1      SF  75.1  75.5  74.9  75.17
2      LA  80.3  84.0  81.3  81.87
3  Boston  63.0  61.0  61.2  61.73
```

Dates

```
print(purchases)
```

```
                  date purchase
0         July 30 2011   $45.08
1     February 01 2011   $19.48
2      January 29 2011   $76.09
3        March 31 2012   $32.61
4     February 05 2011   $75.98
```

Dates

```
purchases["date_converted"] = pd.to_datetime(purchases["date"])
purchases['month'] = purchases["date_converted"].dt.month
print(purchases)
```

```
               date purchase date_converted  month
0      July 30 2011   $45.08     2011-07-30      7
1  February 01 2011   $19.48     2011-02-01      2
2   January 29 2011   $76.09     2011-01-29      1
3     March 31 2012   $32.61     2012-03-31      3
4  February 05 2011   $75.98     2011-02-05      2
```

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Engineering text features

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Extraction

- **Regular expressions:** code to identify patterns

```python
import re
my_string = "temperature:75.6 F"
temp = re.search("\d+\.\d+", my_string)

print(float(temp.group(0)))
```

```
75.6
```

- `\d+`
- `\.`
- `\d+`

Vectorizing text

TF/IDF: Vectorizes words based upon importance

- TF = Term Frequency
- IDF = Inverse Document Frequency

Vectorizing text

```
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
print(documents.head())
```

```
0    Building on successful events last summer and ...
1              Build a website for an Afghan business
2    Please join us and the students from Mott Hall...
3    The Oxfam Action Corps is a group of dedicated...
4    Stop 'N' Swap reduces NYC's waste by finding n...
```

```
tfidf_vec = TfidfVectorizer()
text_tfidf = tfidf_vec.fit_transform(documents)
```

Text classification

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

Let's practice!

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Feature selection

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What is feature selection?

- Selecting features to be used for modeling
- Doesn't create new features
- Improve model's performance

When to select features

city	state	lat	long
hico	tx	31.982778	-98.033333
mackinaw city	mi	45.783889	-84.727778
winchester	ky	37.990000	-84.179722

- Reducing noise
- Features are strongly statistically correlated
- Reduce overall variance

Let's practice!

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Removing redundant features

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Redundant features

- Remove noisy features
- Remove correlated features
- Remove duplicated features

Scenarios for manual removal

city	state	lat	long
hico	tx	31.982778	-98.033333
mackinaw city	mi	45.783889	-84.727778
winchester	ky	37.990000	-84.179722

Correlated features

- Statistically correlated: features move together directionally
- Linear models assume feature independence
- Pearson's correlation coefficient

Correlated features

```
print(df)
```

```
        A     B     C
0    3.06  3.92  1.04
1    2.76  3.40  1.05
2    3.24  3.17  1.03
...
```

```
print(df.corr())
```

```
          A         B         C
A  1.000000  0.787194  0.543479
B  0.787194  1.000000  0.565468
C  0.543479  0.565468  1.000000
```

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Selecting features using text vectors

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Looking at word weights

```
print(tfidf_vec.vocabulary_)
```

```
{'200': 0,
 '204th': 1,
 '33rd': 2,
 'ahead': 3,
 'alley': 4,
 ...
```

```
print(text_tfidf[3].data)
```

```
[0.19392702 0.20261085 ...]
```

```
print(text_tfidf[3].indices)
```

```
[ 31 102  20  70   5 ...]
```

Looking at word weights

```
vocab = {v:k for k,v in
tfidf_vec.vocabulary_.items()}
```

```
print(vocab)
```

```
{0: '200',
 1: '204th',
 2: '33rd',
 3: 'ahead',
 4: 'alley',
 ...
```

```
zipped_row = dict(zip(text_tfidf[3].indices,
                      text_tfidf[3].data))
```

```
print(zipped_row)
```

```
{5: 0.1597882543332701,
 7: 0.26576432098763175,
 8: 0.18599931331925676,
 9: 0.26576432098763175,
 10: 0.13077355258450366,
 ...
```

Looking at word weights

```python
def return_weights(vocab, vector, vector_index):

    zipped = dict(zip(vector[vector_index].indices,
                      vector[vector_index].data))

    return {vocab[i]:zipped[i] for i in vector[vector_index].indices}

print(return_weights(vocab, text_tfidf, 3))
```

```
{'and': 0.1597882543332701,
 'are': 0.26576432098763175,
 'at': 0.18599931331925676,
 ...
```

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Dimensionality reduction

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Dimensionality reduction and PCA

- Unsupervised learning method
- Combines/decomposes a feature space
- Feature extraction - here we'll use to reduce our feature space

- Principal component analysis
- Linear transformation to uncorrelated space
- Captures as much variance as possible in each component

PCA in scikit-learn

```python
from sklearn.decomposition import PCA
pca = PCA()
df_pca = pca.fit_transform(df)

print(df_pca)
```

```
[88.4583, 18.7764, -2.2379, ..., 0.0954, 0.0361, -0.0034],
[93.4564, 18.6709, -1.7887, ..., -0.0509, 0.1331, 0.0119],
[-186.9433, -0.2133, -5.6307, ..., 0.0332, 0.0271, 0.0055]
```

```python
print(pca.explained_variance_ratio_)
```

```
[0.9981, 0.0017, 0.0001, 0.0001, ...]
```

PCA caveats

- Difficult to interpret components
- End of preprocessing journey

Let's practice!

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UFOs and preprocessing

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Identifying areas for preprocessing

Important concepts to remember

- Missing data: `.dropna()` and `.isna()`
- Types: `.astype()`
- Stratified sampling: `train_test_split(X, y, stratify=y)`

Let's practice!

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Categorical variables and standardization

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Categorical variables

```
    state country       type
295    az      us      light
296    tx      us  formation
297    nv      us   fireball
```

- One-hot encoding: `pd.get_dummies()`

Standardization

- `.var()`
- `np.log()`

Let's practice!

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Engineering new features

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UFO feature engineering

date	length_of_time	desc
6/16/2013 21:00	5 minutes	Sabino Canyon Tucson Arizona night UFO sighting.
9/12/2005 22:35	5 minutes	Star like objects hovering in sky, slowly m...
12/31/2013 22:25	3 minutes	Three orange fireballs spotted by witness in E...

- Dates: `.dt.month` or `.dt.hour` attributes
- Regex: `\d` and `.group()`
- Text: tf-idf and `TfidfVectorizer`

Let's practice!

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Feature selection and modeling

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Feature selection and modeling

- Redundant features
- Text vector

Final thoughts

- Iterative processes
- Know your dataset
- Understand your modeling task

Let's practice!

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Congratulations!

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What you've learned

- Preparing data for modeling:
  - Missing data
  - Incorrect types
  - Standardize numerical values
  - Process categorical values
  - Feature engineering
  - Select features for modeling

Let's practice!

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