Feature selection

PREPROCESSING FOR MACHINE LEARNING IN PYTHON





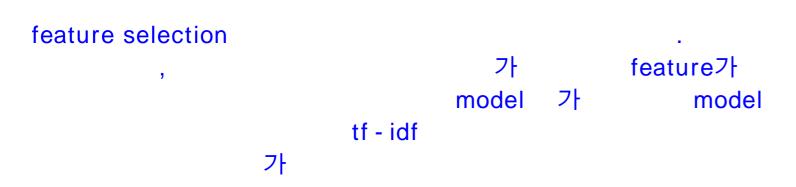
What is feature selection?

- 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







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 correlation coefficient



Correlated features

```
print(df)
       Α
             В
    3.06 3.92 1.04
                                                                                                    가
          3.40
    2.76
               1.05
    3.24 3.17 1.03
                                                                                    "corr"
                                                                                                   가 1(0.78)
                                                                         가
print(df.corr())
         Α
   1.000000
            0.787194
                      0.543479
  0.787194
           1.000000
                      0.565468
  0.543479 0.565468 1.000000
```



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 0.24915 0.31957651 0.18599931 ...]

print(text_tfidf[3].indices)

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

Adatacamp

Looking at word weights

```
vocab = {v:k for k,v in
                                     zipped_row =
  tfidf_vec.vocabulary_.items()}
                                     dict(zip(text_tfidf[3].indices,
                                     text_tfidf[3].data))
print(vocab)
                                     print(zipped_row)
{0: '200',
                                     {5: 0.1597882543332701,
1: '204th',
2: '33rd',
                                       7: 0.26576432098763175,
                                       8: 0.18599931331925676,
3: 'ahead',
4: 'alley',
                                       9: 0.26576432098763175,
                                       10: 0.13077355258450366,
```

Adatacamp

가

Looking at word weights

```
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))
                                                                                     , text_tfidf
{'and': 0.1597882543332701,
 'are': 0.26576432098763175,
 'at': 0.18599931331925676,
```



(dimensionality reduction)

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

```
from sklearn.decomposition import PCA
pca = PCA()
                                                                           PCA
df_pca = pca.fit_transform(df)
                                                                                       , skikit - learn pca
print(df_pca)
                                                                                                       tf - idf
                                                                            pca
                                                                                       PCA
[88.4583, 18.7764, -2.2379, \ldots, 0.0954, 0.0361, -0.0034],
                                                                                        PCA
[93.4564, 18.6709, -1.7887, \ldots, -0.0509, 0.1331, 0.0119],
                                                                            skikit - learn PCA
[-186.9433, -0.2133, -5.6307, \ldots, 0.0332, 0.0271, 0.0055]
print(pca.explained_variance_ratio_)
[0.9981, 0.0017, 0.0001, 0.0001, ...]
```



PCA caveats

- Difficult to interpret components
- End of preprocessing journey



