2-dimensionality-reduction

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0.1 Dimensionality Reduction

This notebook investigate whether the data preprocessing technique dimensionality reduction can affect the final classification performance.

0.1.1 1. Data Preprocessing

```
In [2]: pos_examples = [s.decode("utf-8", "ignore").strip() for s in list(open(helper.mr_pos_d)
        neg_examples = [s.decode("utf-8", "ignore").strip() for s in list(open(helper.mr_neg_decode("utf-8", "ignore").strip())
        pos_nums, neg_nums = len(pos_examples), len(neg_examples)
        x = pos_examples + neg_examples
        x = [helper.clean_str(sentence) for sentence in x]
        pos_labels = [1 for _ in range(pos_nums)]
        neg_labels = [0 for _ in range(neg_nums)]
        y = pos_labels + neg_labels
        x, y = np.array(x), np.array(y)
        x_train, y_train, x_dev, y_dev = helper.split_train_dev(x, y)
        # TF-IDF
        tfidf = TfidfVectorizer(min_df=2, ngram_range=(1,2))
        tfidf.fit(x_train)
        x_train_tf = tfidf.transform(x_train).toarray()
        x_dev_tf = tfidf.transform(x_dev).toarray()
        # PCA
```

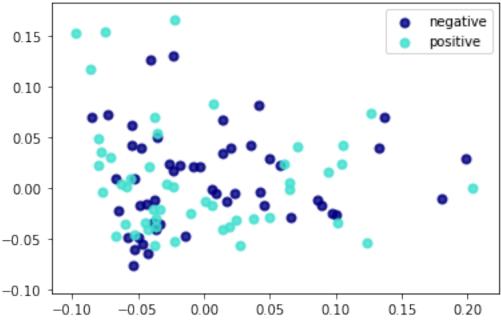
```
pca = PCA(n_components=2)
x_train_pca = pca.fit(x_train_tf).transform(x_train_tf)
```

0.1.2 2. Reducetion 2-dim

```
In [3]: x_pca, y_pca = x_train_pca[:100], y_train[:100]
    plt.figure()
    colors = ['navy', 'turquoise']
    labels = ['negative', 'positive']

for color, i, label in zip(colors, [0, 1], labels):
    plt.scatter(x_pca[y_pca == i, 0], x_pca[y_pca == i, 1], color=color, alpha=.8, lw=:
    plt.legend(loc='best', shadow=False, scatterpoints=1)
    plt.title('PCA of Moive Review dataset (d = 2)')
```





0.1.3 3. Can dimensionality reduction technique affect the classification performance?

We use the best performance classify linear svc as the baseline in this experiment. In this case, the accuracy drop with the decrement of size of features, interpreting that the dimensionality reduction may lose the information of the original dataset.

```
x_tf = tfidf.transform(x).toarray()
            pca = PCA(n_components=d)
            x_pca = pca.fit(x_tf).transform(x_tf)
            x_train_tf, y_train, x_dev_tf, y_dev = helper.split_train_dev(x_pca, y)
            svc = LinearSVC()
            svc.fit(x_train_tf, y_train)
            predicted = svc.predict(x_dev_tf)
            print("Accuracy: {0:.4f}".format(metrics.accuracy_score(predicted, y_dev)))
            print(metrics.classification_report(predicted, y_dev))
Accuracy: 0.7655
                          recall f1-score
             precision
                                             support
          0
                  0.76
                            0.77
                                      0.77
                                                  535
                  0.77
                            0.76
          1
                                      0.76
                                                  531
                            0.77
                                      0.77
                                                 1066
avg / total
                  0.77
Accuracy: 0.7439
             precision
                          recall f1-score
                                             support
          0
                  0.74
                            0.75
                                      0.75
                                                  532
          1
                  0.75
                            0.74
                                      0.74
                                                  534
                                                 1066
avg / total
                  0.74
                            0.74
                                      0.74
Accuracy: 0.6829
             precision
                          recall f1-score
                                             support
          0
                  0.64
                            0.70
                                      0.67
                                                  491
          1
                  0.72
                            0.66
                                      0.69
                                                  575
                            0.68
                                      0.68
                                                 1066
avg / total
                  0.69
```