Lab2

September 30, 2021

[ ]:
```
import numpy as np
import pandas as pd
import sklearn
from sklearn.metrics import confusion_matrix, accuracy_score, make_scorer
from sklearn.model_selection import cross_validate, cross_val_score,␣
↪cross_val_predict, GridSearchCV, RandomizedSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
import matplotlib
import matplotlib.pyplot as plt
import warnings

warnings.simplefilter(action='ignore', category=pd.errors.PerformanceWarning)
```

1 Assignment 1.1

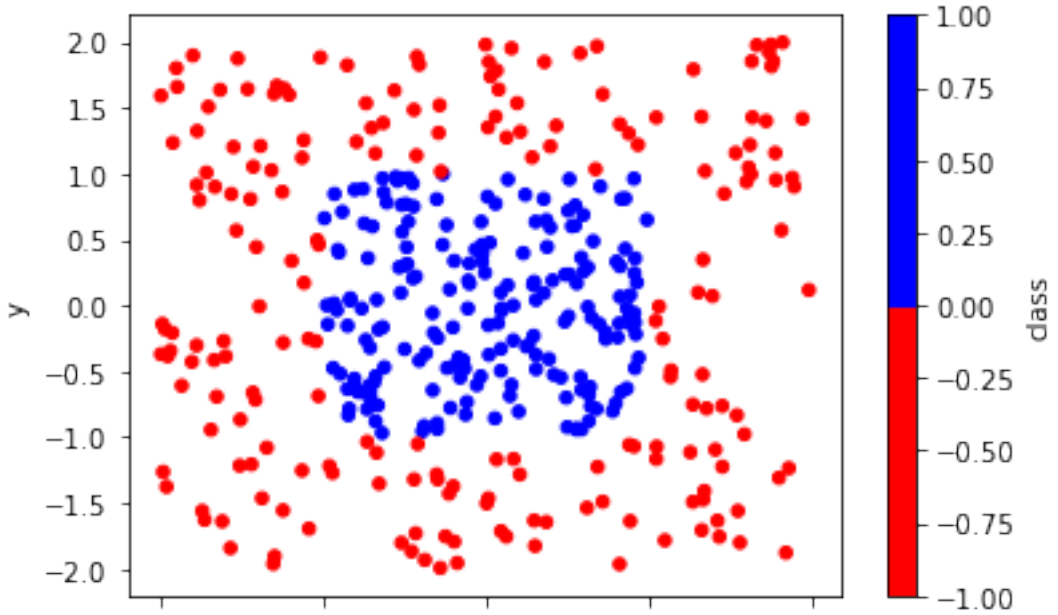
[ ]:
```
exp1a = pd.read_csv('exp1a.csv')
exp1a.name = 'exp1a'
exp1b = pd.read_csv('exp1b.csv')
exp1b.name = 'exp1b'
exp1c = pd.read_csv('exp1c.csv')
exp1c.name = 'exp1c'
```

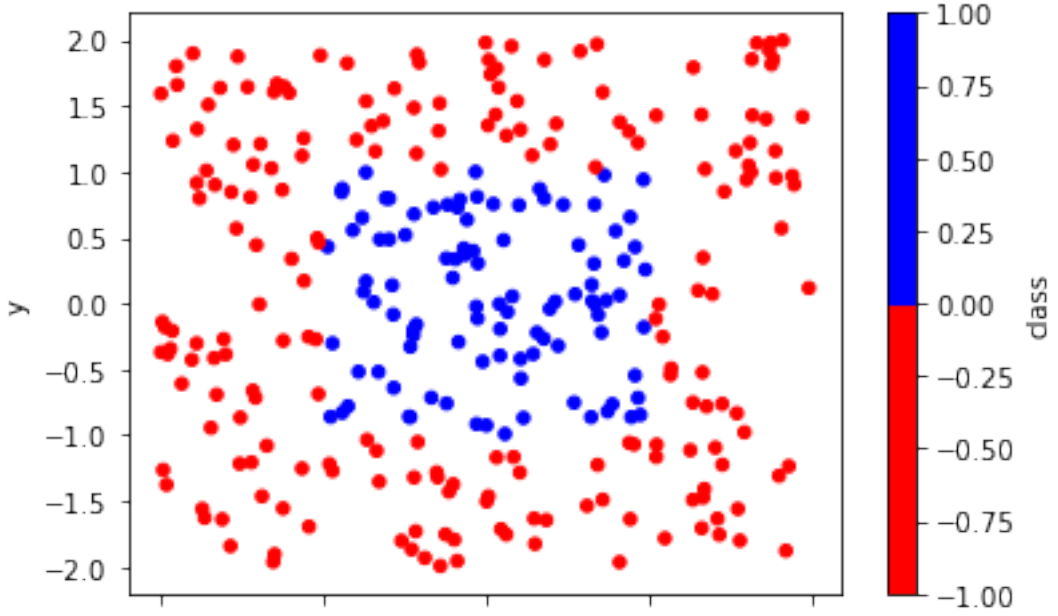
1.1 (a)

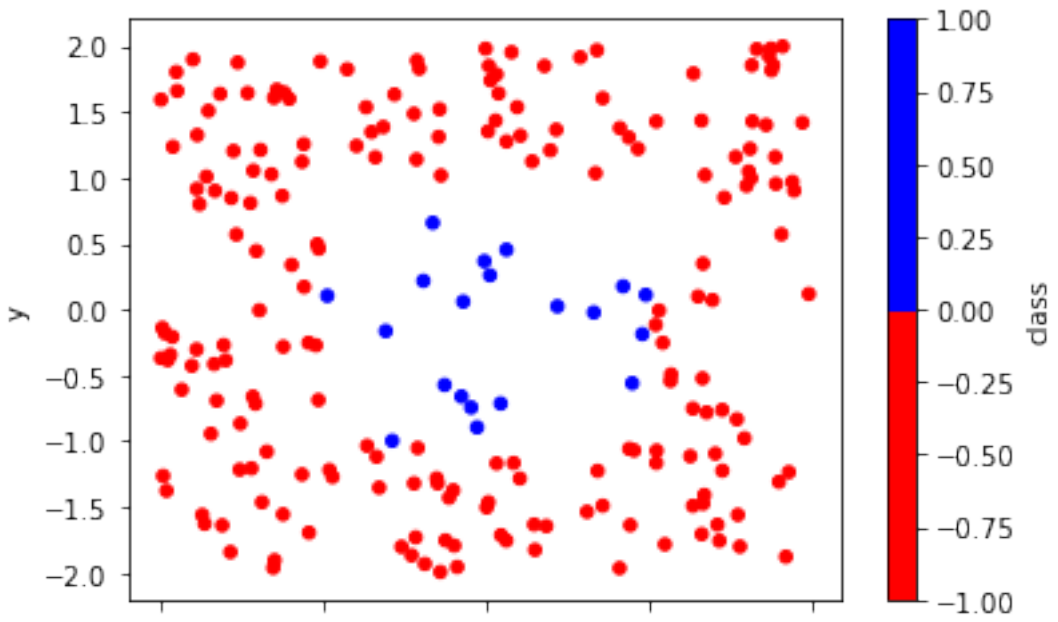
Visualize the data sets from Experiment 1

[ ]:
```
cmap = matplotlib.colors.ListedColormap(['red', 'blue'])
exp1a.plot.scatter('x','y', c='class', cmap=cmap)
exp1b.plot.scatter('x','y', c='class', cmap=cmap)
exp1c.plot.scatter('x','y', c='class', cmap=cmap)
```

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe19a995f10>
```


2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
y
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
dass


2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
y
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
dass



1.2 (b) and (c)

For each fo the data sets, how does the 10-fold cross-validation accuracy rates and confusion matrices vary as k increases? Explain this trend.

[ ]:
```
idx = [
    np.array([1, 1, 5, 5, 11, 11, 21, 21]),
    np.array(['positive', 'negative'] * 4)
    ]

cols = [
    np.concatenate([[i] * 3 for i in ['exp1a', 'exp1b', 'exp1c']]),
    ['confusion matrix', 'confusion matrix', 'accuracy'] * 3,
    ['positive', 'negative', ''] * 3
    ]
results_b_c = pd.DataFrame(columns=cols, index=idx)

results_b_c.index.names = ['k', 'predicted']
for exp in [exp1a, exp1b, exp1c]:
    for k in [1,5,11,21]:
        knn = KNeighborsClassifier(n_neighbors=k)
        y_predict = cross_val_predict(knn, exp[['x', 'y']].values,␣
↪exp['class'], cv=10)
        results_b_c.loc[k,(exp.name, 'confusion matrix')] =␣
↪confusion_matrix(exp['class'], y_predict)
```

```
        results_b_c.loc[k,(exp.name, 'accuracy')] =␣
↪accuracy_score(exp['class'], y_predict)
results_b_c
```

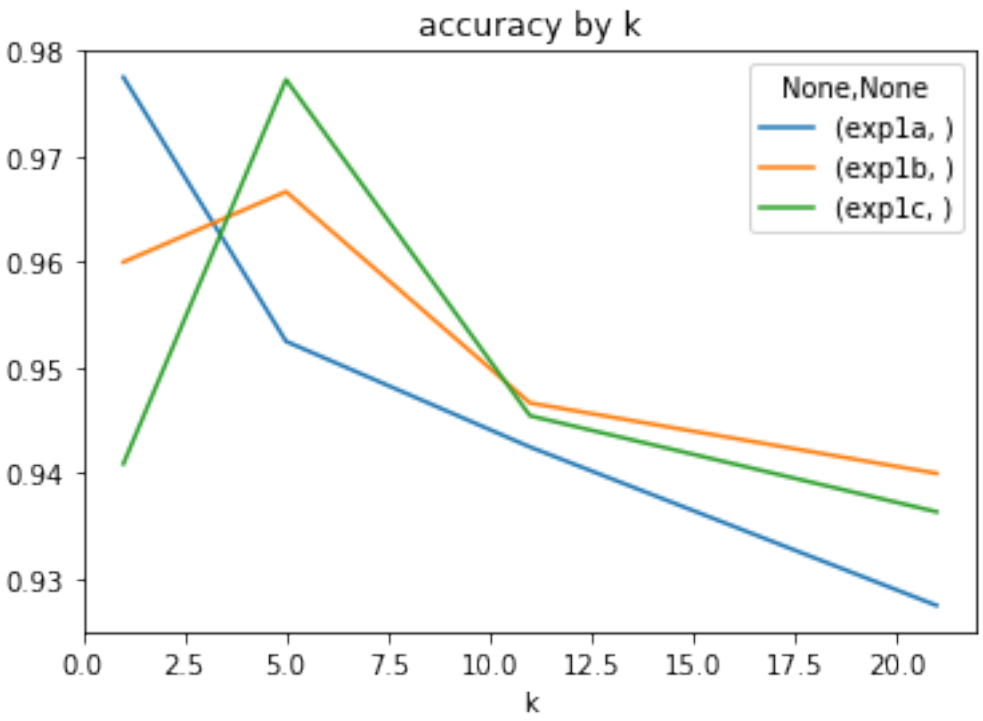
[ ]:

		exp1a			exp1b		\
		confusion matrix		accuracy	confusion matrix		
		positive	negative		positive	negative	
k	predicted						
1	positive	194	6	0.9775	193	7	
	negative	3	197	0.9775	5	95	
5	positive	183	17	0.9525	194	6	
	negative	2	198	0.9525	4	96	
11	positive	177	23	0.9425	190	10	
	negative	0	200	0.9425	6	94	
21	positive	171	29	0.9275	190	10	
	negative	0	200	0.9275	8	92	

		exp1c			
		accuracy	confusion matrix		accuracy
			positive	negative	
k	predicted				
1	positive	0.96	194	6	0.940909
	negative	0.96	7	13	0.940909
5	positive	0.966667	200	0	0.977273
	negative	0.966667	5	15	0.977273
11	positive	0.946667	200	0	0.945455
	negative	0.946667	12	8	0.945455
21	positive	0.94	200	0	0.936364
	negative	0.94	14	6	0.936364

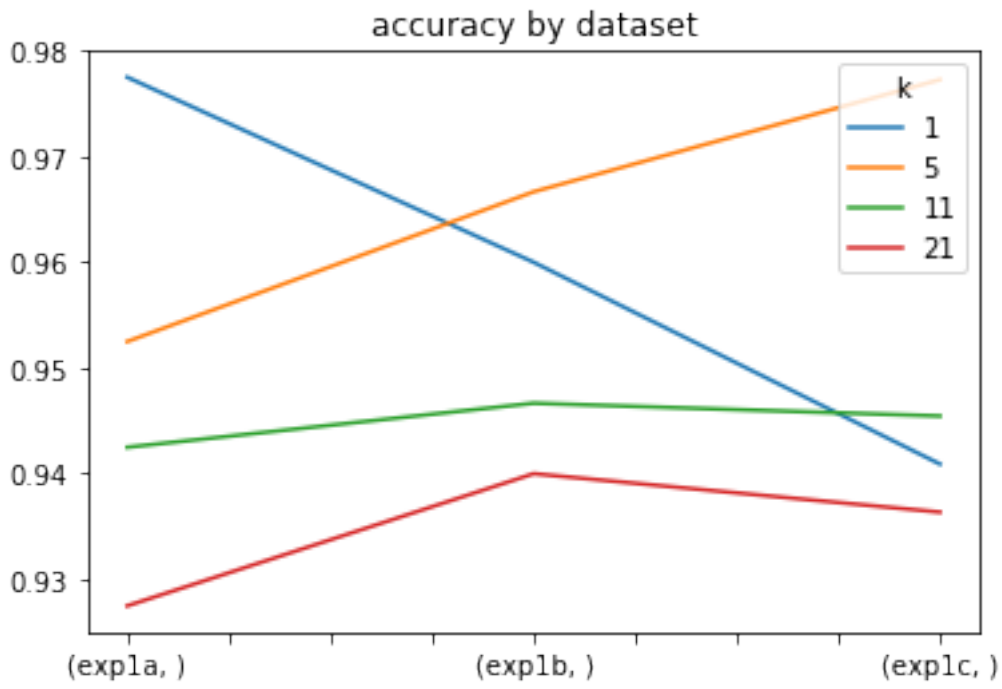
[ ]:
```
(results_b_c
    .select_dtypes(object)
    .astype(float)
    .xs('accuracy', axis=1, level=1)
    .groupby('k', level=0, axis=0)
    .agg('mean')
).plot.line(title='accuracy by k')
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe19adc4b80>



[ ]:
```
(results_b_c
    .select_dtypes(object)
    .astype(float)
    .xs('accuracy', axis=1, level=1)
    .groupby('k', level=0, axis=0)
    .agg('mean')
).T.plot.line(title='accuracy by dataset')
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe19af647c0>



As we can see with increasing k the accuracy drops for all data sets. However, it's important to notice, that for set exp1b and exp1c there is a spike for k=5. This can be explained by the fact that with increasing k we decrease the flexibility of the model and hence increase the bias (while decreasing the variance). According to the recorded accuracy values it can be assumed that the best tradeoff between bias and variance is at about k=5. It's also interesting to see, that the different data sets yield different results for different k values. From the chart 'accuracy by dataset' we can clearly see, the different k-values yield different results for different data sets. Whereas k=11 performs only third best for exp1a and exp1b it performs second best for exp1c.

1.3 (d)

[ ]:
```
idx = [
    np.array([1, 1, 5, 5, 11, 11, 21, 21]),
    np.array(['positive', 'negative'] * 4)
    ]

cols = [
    np.concatenate([[i] * 3 for i in ['exp1a', 'exp1b', 'exp1c']]),
    ['confusion matrix', 'confusion matrix', 'accuracy'] * 3,
    ['positive', 'negative', ''] * 3
    ]
results_d = pd.DataFrame(columns=cols, index=idx)
results_d.index.names = ['k', 'predicted']
for exp in [exp1a, exp1b, exp1c]:
    for k in [1,5,11,21]:
```

```
        knn = KNeighborsClassifier(n_neighbors=k, weights='distance')
        y_predict = cross_val_predict(knn, exp[['x', 'y']].values, exp['class'].
 ↪values, cv=10)
        results_d.loc[k,(exp.name, 'confusion matrix')] =␣
 ↪confusion_matrix(exp['class'], y_predict)
        results_d.loc[k,(exp.name, 'accuracy')] = accuracy_score(exp['class'],␣
 ↪y_predict)
results_d
```

[ ]:

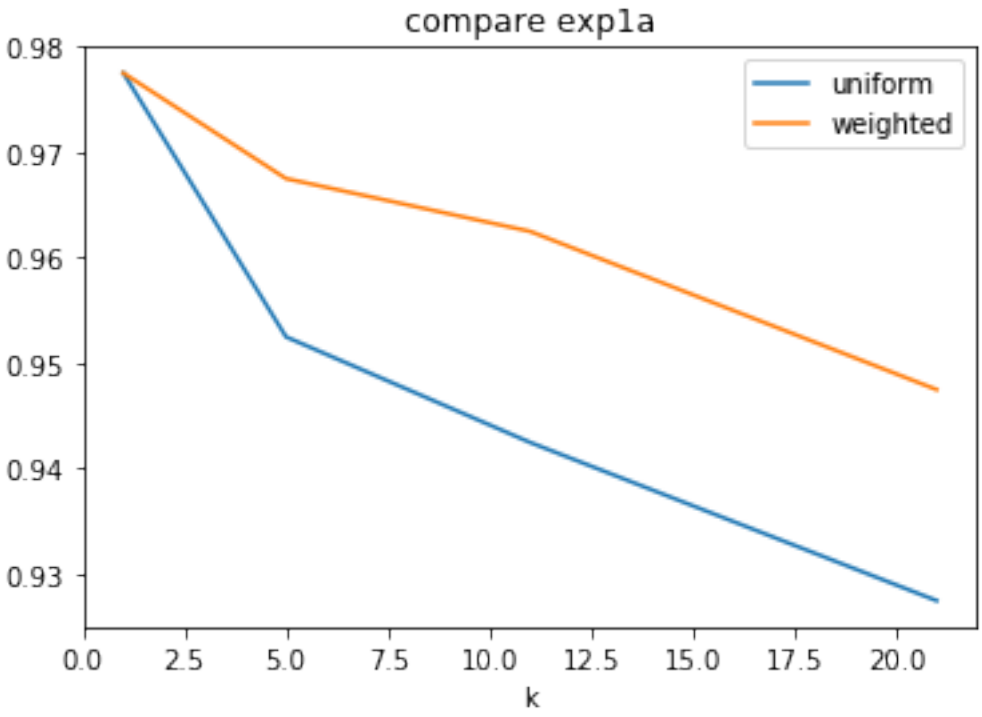
		exp1a			exp1b		\
		confusion matrix		accuracy	confusion matrix		
		positive	negative		positive	negative	
k	predicted						
1	positive	194	6	0.9775	193	7	
	negative	3	197	0.9775	5	95	
5	positive	189	11	0.9675	195	5	
	negative	2	198	0.9675	4	96	
11	positive	186	14	0.9625	194	6	
	negative	1	199	0.9625	6	94	
21	positive	179	21	0.9475	193	7	
	negative	0	200	0.9475	4	96	

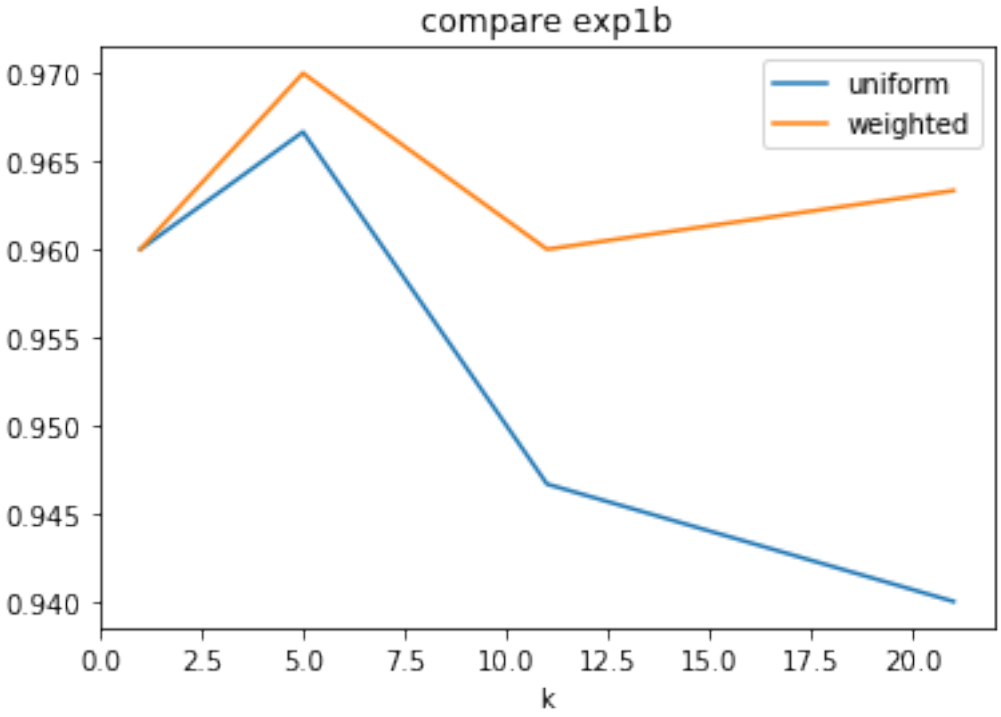
		exp1c			
		accuracy	confusion matrix		accuracy
			positive	negative	
k	predicted				
1	positive	0.96	194	6	0.940909
	negative	0.96	7	13	0.940909
5	positive	0.97	200	0	0.977273
	negative	0.97	5	15	0.977273
11	positive	0.96	200	0	0.968182
	negative	0.96	7	13	0.968182
21	positive	0.963333	200	0	0.968182
	negative	0.963333	7	13	0.968182

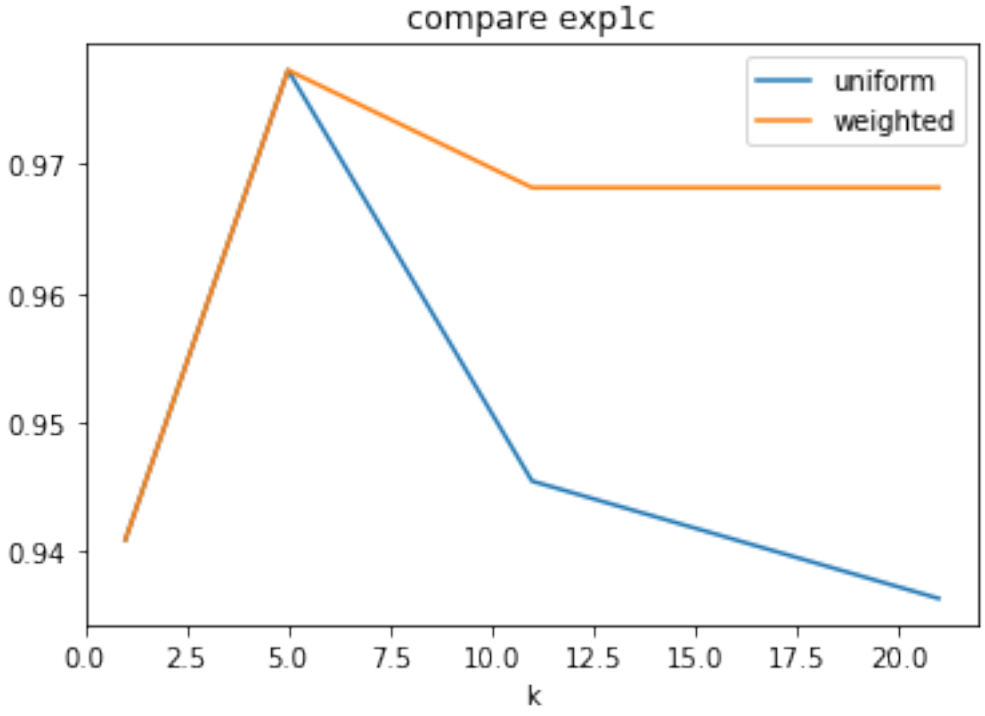
[ ]:
```
compare_results = pd.concat(
    (results_b_c.select_dtypes(object).astype(float).xs('accuracy', axis=1,␣
 ↪level=1).groupby('k', level=0, axis=0).agg('mean'),
    results_d.select_dtypes(object).astype(float).xs('accuracy', axis=1,␣
 ↪level=1).groupby('k', level=0, axis=0).agg('mean')
    )
    , axis=1
)
compare_results.columns = ['exp1a', 'exp1b', 'exp1c', 'exp1a_d', 'exp1b_d',␣
 ↪'exp1c_d']

for i in ['a', 'b', 'c']:
```

```
    temp = compare_results[[f'exp1{i}', f'exp1{i}_d']]
    temp.columns = ['uniform', 'weighted']
    temp.plot.line(title=f'compare exp1{i}')
```




compare exp1b
uniform
weighted
0.970
0.965
0.960
0.955
0.950
0.945
0.940
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
k


compare exp1c
uniform
weighted
0.97
0.96
0.95
0.94
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
k

In the plot 'compare results from b and d' we can see that the classifier using the weighted kNN approach perform better (or equal for exp1c) for all values of k. For the 'uniform' approach (where all neighbors are weighted equally) we see a bad generalization performance for increasing k. The 'weighted' approach on the other hand performs better for greater k. It is assumed, that this is because close neighbors are better indicators for the class than neighbors with a greater distance. Additionally we have to consider that these data sets are noise free. So for this example it can be concluded, that weighted distances generalize better.

1.4 (e)

run decision trees and logistic regression on the data sets

[ ]:
```
cols = [
    ['exp1a', 'exp1a', 'exp1a' ,'exp1b', 'exp1b', 'exp1b', 'exp1c', 'exp1c',␣
 ↪'exp1c'],
    ['confusion matrix', 'confusion matrix', 'accuracy'] * 3,
    ['positive', 'negative', ''] * 3
    ]

idx = [
    np.concatenate([([i]*2) for i in ['Decision Trees', 'Logistic␣
 ↪Regression']], axis=0),
    # np.array(['decision tree', 'decision tree', 'logistic regression',␣
 ↪'logistic regression']),
    np.array(['positive', 'negative'] * 2)
    ]

results_e = pd.DataFrame(columns=cols, index = idx)

results_e.index.names = ['classifier', 'predicted']
for exp in [exp1a, exp1b, exp1c]:
    des_tree = DecisionTreeClassifier(criterion='entropy')
    log_reg = LogisticRegression()
    y_predict_tree = cross_val_predict(des_tree, exp[['x','y']], exp['class'])
    y_predict_log_reg = cross_val_predict(log_reg, exp[['x','y']], exp['class'])
    results_e.loc['Decision Trees',(exp.name, 'confusion matrix')] =␣
 ↪confusion_matrix(exp['class'], y_predict_tree)
    results_e.loc['Logistic Regression',(exp.name, 'confusion matrix')] =␣
 ↪confusion_matrix(exp['class'], y_predict_log_reg)
    results_e.loc['Decision Trees',(exp.name, 'accuracy')] =␣
 ↪accuracy_score(exp['class'], y_predict_tree)
    results_e.loc['Logistic Regression',(exp.name, 'accuracy')] =␣
 ↪accuracy_score(exp['class'], y_predict_log_reg)
results_e
```

[ ]:
```
                                        exp1a                    \
                                confusion matrix          accuracy
```

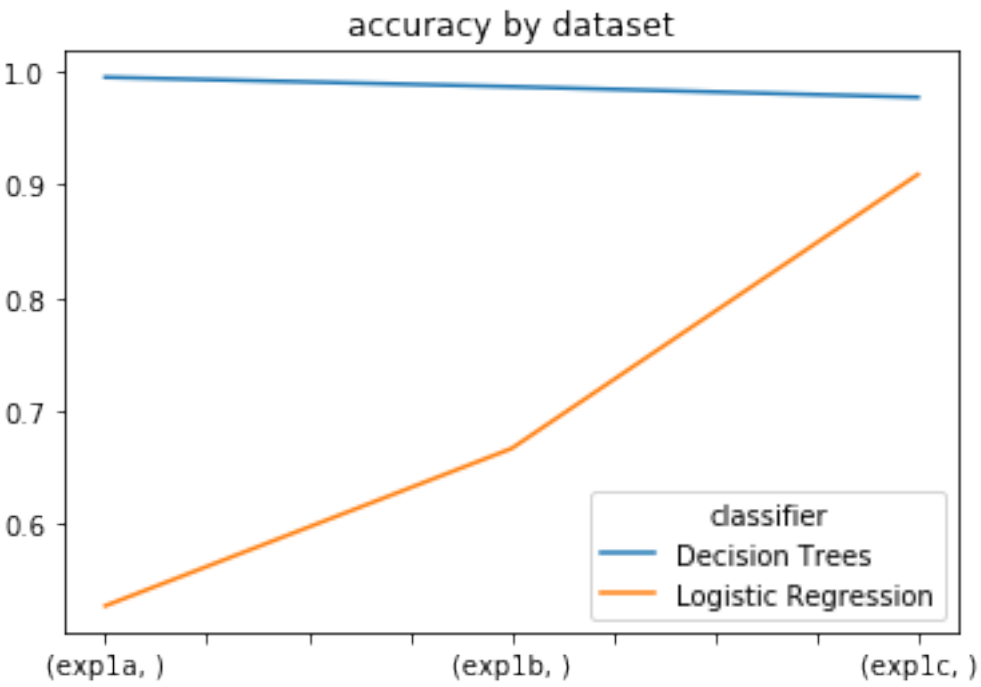
```
                                          positive negative
classifier          predicted
Decision Trees      positive                   200        0    0.995
                    negative                     2      198    0.995
Logistic Regression positive                   104       96   0.5275
                    negative                    93      107   0.5275

                                             exp1b                    \
                                   confusion matrix           accuracy
                                          positive negative
classifier          predicted
Decision Trees      positive                   200        0  0.986667
                    negative                     4       96  0.986667
Logistic Regression positive                   200        0  0.666667
                    negative                   100        0  0.666667

                                             exp1c
                                   confusion matrix           accuracy
                                          positive negative
classifier          predicted
Decision Trees      positive                   200        0  0.977273
                    negative                     5       15  0.977273
Logistic Regression positive                   200        0  0.909091
                    negative                    20        0  0.909091
```

[ ]:
```
(results_e
    .select_dtypes(object)
    .astype(float)
    .xs('accuracy', axis=1, level=1)
    .groupby('classifier', level=0, axis=0)
    .agg('mean')
).T.plot.line(title='accuracy by dataset')
```

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe19b307d00>
```



The data in experiment 1 does not follow a linear distribution. Hence, the logistic regression yields worse results than the decision trees. Decision trees work very well on this type of data, since the decision boundaries are parallel to the axis of the coordinate system. When looking at the chart 'accuracy by dataset' we can see, that for the exp1c we get way better results than for exp1a and exp1b. This is probably because the exp1c is the most imbalanced one. Whereas exp1a is split in equal proportions. Hence, we recieve for exp1a an accuracy score below 0.6. This underscores the impact an unbalanced dataset can have on the classification accuracy score.

2 Assignment 1.2

to improve the performance of SVC/logistic regression and get fitting and prediction results in a reasonable amount of time I implemented the standard scaler. This is especially important for the exp2b data set.

[ ]:
```
exp2a = pd.read_csv('exp2a.csv')
exp2a.name = 'exp2a'
exp2b = pd.read_csv('exp2b.csv')
exp2b.name = 'exp2b'
```

[ ]:
```
des_tree = DecisionTreeClassifier(criterion='entropy')
knn = KNeighborsClassifier()
gau_nav_bay = GaussianNB()
log_reg = LogisticRegression()
svm_clf = SVC(kernel='linear')
```

2.1 (a)

which classifiers have a good, which have a bad gernalization performance?

[ ]:
```
def get_evaluation(data_set, classifier_):
    classifier_names = [str(j.__class__).split('.')[-1][:-2] for j in␣
 ↪classifier_]
    cols = [
        np.concatenate([([i.name]*3) for i in [data_set]], axis=0),
        ['confusion matrix', 'confusion matrix', 'accuracy']*1,
        [1, 2, '']*1
        ]
    idx = [
        np.concatenate([([i]*2) for i in classifier_names], axis=0),
        [1, 2] * len(classifier_names)
    ]
    results = pd.DataFrame(columns=cols, index = idx)
    results.index.names = ['classifier', 'actual']

    X = data_set.iloc[:,:-1].values
    y = data_set.iloc[:,-1].values


    for clf in classifier_:
            clf_name = str(clf.__class__).split('.')[-1][:-2]
            y_predict = cross_val_predict(clf, X, y)
            cm = confusion_matrix(y, y_predict)
            acc = accuracy_score(y, y_predict)
            results.loc[clf_name,(data_set.name, 'confusion matrix')] = cm
            results.loc[clf_name,(data_set.name, 'accuracy')] = acc

    return results

get_evaluation(exp2a, [des_tree, knn, gau_nav_bay, log_reg, svm_clf])
```

[ ]:

		exp2a		
		confusion matrix		accuracy
		1	2	
classifier	actual			
DecisionTreeClassifier	1	550	0	1.0
	2	0	551	1.0
KNeighborsClassifier	1	550	0	1.0
	2	0	551	1.0
GaussianNB	1	0	550	0.02634
	2	522	29	0.02634
LogisticRegression	1	0	550	0.02634
	2	522	29	0.02634
SVC	1	220	330	0.499546

```
2                    221   330   0.499546
```

We can see, that Decision Tree and KNN are quite successfull. It has to be assumed that both classifiers are heavily overfitted. However, as the dataset is noise-free this is no real problem for this use case. GausianNB as well as Logistic Regression on the other hand perform incredibly bad. This is probably due to the fact that both classes themselves consist of two independent blocks each which are contrary to one another. However, the SVC employing a lilnear kernel is also able to seperate the two classes inan acceptable fashion. Therefore it's somewhat suprising, that GausianNB and LogisticRegression perform this poorly. In Fact, the results for GausianNB and LogisticRegression are so bad that the replacement of a predicted class with the other class provides an almost perfect classifier. Given that observation it seems likely that there is some bug in the code. Sadly I've not been able to spot it yet.

2.2 (b)

Gausian Gausian Naive Bayes, Logistic Regression and SVC show an accuracy that could be improved. I'll use GridSearchCV to search for better hyper-parameter.

2.2.1 Gausian Naive Bayes

[ ]:
```
X = exp2a.iloc[:,:-1].values
y = exp2a.iloc[:,-1].values

list_improved_clf = []
gs_gnb = GridSearchCV(gau_nav_bay, {'var_smoothing': np.logspace(300,0,␣
 ↪num=200)}, cv=10, n_jobs=-1)
gs_gnb.fit(X, y)
improved_clfs = [gs_gnb]
gs_gnb.best_params_
```

[ ]:
```
{'var_smoothing': 1e+300}
```

2.2.2 Logistic Regression

[ ]:
```
space = dict()
space['solver'] = ['newton-cg', 'lbfgs', 'liblinear']
space['penalty'] = ['none', 'l1', 'l2', 'elasticnet']
space['C'] = np.logspace(-5,5, num=20)
model = LogisticRegression()

# disable warnings to increase readability. Some combinations of penalty asd C␣
 ↪values produce errors.
warnings.simplefilter(action='ignore', category=UserWarning)
warnings.simplefilter(action='ignore', category=sklearn.exceptions.
 ↪FitFailedWarning)
```

```
gs_lr = RandomizedSearchCV(model, space, cv=10, n_jobs=-1, n_iter=500,␣
 ↪scoring='accuracy', error_score=0)
gs_lr.fit(X,y)
improved_clfs.append(gs_lr)

warnings.simplefilter(action='default', category=UserWarning)
warnings.simplefilter(action='default', category=sklearn.exceptions.
 ↪FitFailedWarning)

gs_lr.best_params_
```

[ ]: {'solver': 'liblinear', 'penalty': 'l1', 'C': 1e-05}

2.2.3 SVC

[ ]:
```
space = dict()
space['kernel'] = ['linear', 'poly', 'rbf', 'sigmoid']
scaler = StandardScaler()
X_transform = scaler.fit_transform(X)
gs_svm = GridSearchCV(svm_clf, param_grid=space, cv=10, scoring='accuracy',␣
 ↪n_jobs=-1)
gs_svm.fit(X_transform,y)
improved_clfs.append(gs_svm)
gs_svm.best_params_
```

[ ]: {'kernel': 'poly'}

2.2.4 Accuracy comparison

[ ]:
```
old_acc = (
    get_evaluation(exp2a, [gau_nav_bay, log_reg, svm_clf])
        .select_dtypes(object)
        .astype(float)
        .xs('accuracy', 1, 1)
        .groupby('classifier', 0)
        .agg('mean')
    )

new_acc = (
    get_evaluation(exp2a, [i.best_estimator_ for i in improved_clfs])
        .select_dtypes(object)
        .astype(float)
        .xs('accuracy', 1, 1)
        .groupby('classifier', 0)
        .agg('mean')
    ).merge(old_acc, left_index=True, right_index=True)
```

```
new_acc.columns = ['new acc', 'old acc']

new_acc.assign(difference = lambda x: x['new acc'] - x['old acc'])
```

[ ]:

classifier	new acc	old acc	difference
GaussianNB	0.499546	0.026340	0.473206
LogisticRegression	0.499546	0.026340	0.473206
SVC	1.000000	0.499546	0.500454

it can be seen that the change of the hyperparameters has a tremendous effect on the accuracy of the classifiers.

2.3 (c) and (d)

[ ]:
```
cols = [
    np.concatenate([([i]*3) for i in ['exp2a', 'exp2b']], axis=0),
    ['confusion matrix', 'confusion matrix', 'accuracy']*2,
    ['positive', 'negative', '']*2
    ]
idx = [
    np.concatenate([([str(i.__class__).split('.')[-1][:-2]]*2) for i in␣
 ↪[des_tree, knn, gau_nav_bay, log_reg, svm_clf]], axis=0),
    ['positive', 'negative'] * 5
]
results_2_c_d = pd.DataFrame(columns=cols, index = idx)
results_2_c_d.index.names = ['classifier', 'actual']


for exp in [exp2a, exp2b]:
    X = exp.iloc[:, :-1].values
    y = exp.iloc[:,-1].values

    scaler = StandardScaler()
    X = scaler.fit_transform(X)

    for clf in [des_tree, knn, gau_nav_bay, log_reg, svm_clf]:
        name = str(clf.__class__).split('.')[-1][:-2]
        y_predict = cross_val_predict(clf, X, y)
        cm = confusion_matrix(y, y_predict)
        acc = accuracy_score(y, y_predict)
        results_2_c_d.loc[name,(exp.name, 'confusion matrix')] = cm
        results_2_c_d.loc[name,(exp.name, 'accuracy')] = acc
results_2_c_d
```

[ ]:

	exp2a	\
	confusion matrix	accuracy

		positive	negative	
classifier	actual			
DecisionTreeClassifier	positive	550	0	1.0
	negative	0	551	1.0
KNeighborsClassifier	positive	550	0	1.0
	negative	0	551	1.0
GaussianNB	positive	0	550	0.02634
	negative	522	29	0.02634
LogisticRegression	positive	0	550	0.02634
	negative	522	29	0.02634
SVC	positive	220	330	0.499546
	negative	221	330	0.499546

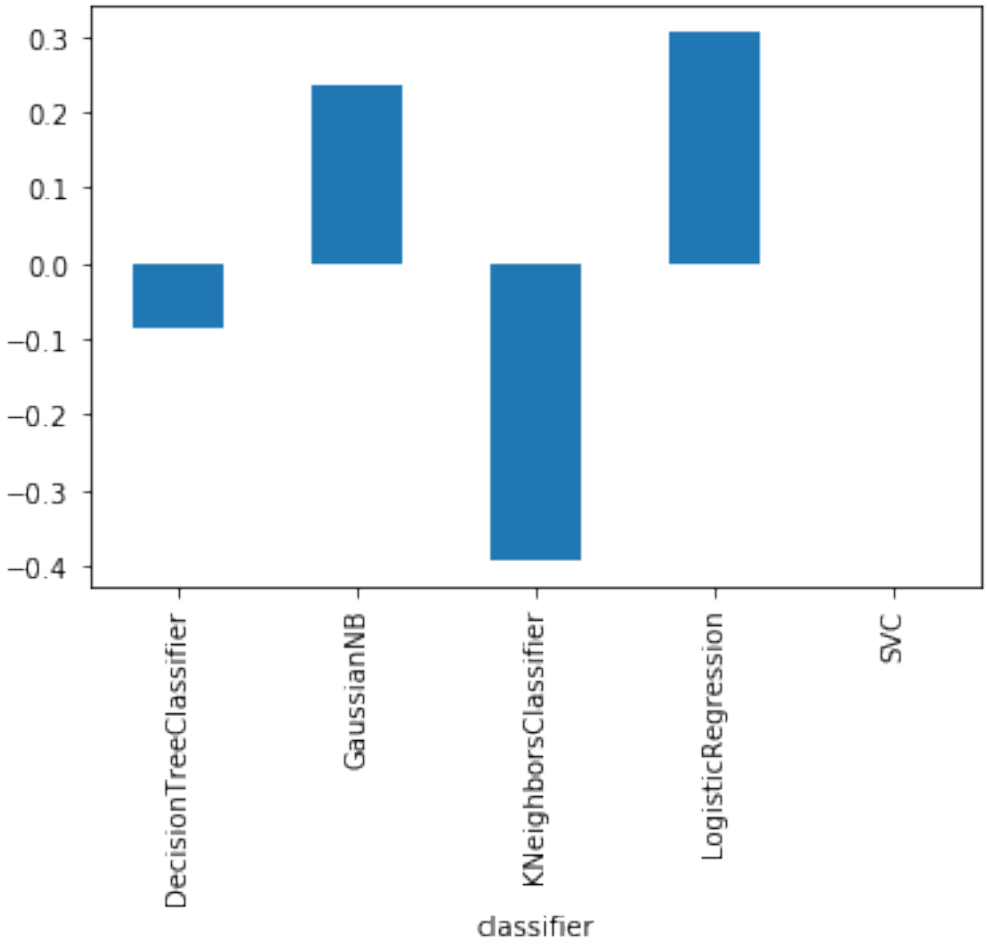
		exp2b		
		confusion matrix		accuracy
		positive	negative	
classifier	actual			
DecisionTreeClassifier	positive	499	51	0.912807
	negative	45	506	0.912807
KNeighborsClassifier	positive	361	189	0.608538
	negative	242	309	0.608538
GaussianNB	positive	132	418	0.26158
	negative	395	156	0.26158
LogisticRegression	positive	175	375	0.331517
	negative	361	190	0.331517
SVC	positive	269	281	0.499546
	negative	270	281	0.499546

[ ]:
```
accuracy_comp = (
    results_2_c_d
        .select_dtypes(object)
        .astype(float)
        .xs('accuracy', axis=1, level=1)
        .groupby('classifier', level=0, axis=0)
        .agg('mean')
        .assign(difference = lambda x: x['exp2b'] - x['exp2a'])
    )
accuracy_comp['difference'].plot.bar()
accuracy_comp
```

[ ]:

	exp2a	exp2b	difference
classifier			
DecisionTreeClassifier	1.000000	0.912807	-0.087193
GaussianNB	0.026340	0.261580	0.235241
KNeighborsClassifier	1.000000	0.608538	-0.391462
LogisticRegression	0.026340	0.331517	0.305177

```
SVC                    0.499546   0.499546    0.000000
```



Given the fact that the dataset was enriched by adding noisy features, sampled from a totally unreleated distribution it's suprising to see that in fact some classifiers worked even better than expected.

- Decision Trees
  - decrease can most likely be explained by noisy variables making it harder to generate linear decision boundaries parallel to axes. On the other hand that decrease is suprising, as the decision tree employs embedded feature selection, which should root out (at least part of) the noisy variables added to the set.
- Gausian Naive Bayes
  - In 1.2(b) it was shown, that the performance of the Naive Bayes Classifier is influenced by the parameter 'var_smoothing'. Given the increased number of features and the non-linearity of the resulting data set it's supprising, that the NaiveBayes Classifier reaches a better result for exp2b, than for exp2a
- Logistic Regression
  - In 1.2(b) it was shown, that the Logistic Regression can be heavily optimized using

many different parameters. The implementation as shown in Table 1 is simply not optimal. However, the increase in performance is still suprising, given that the added noisy features dont contribute to the linearity of the data-set it's suprising that the logistic regression yields better results for exp2b than for exp2a.

- Nearest Neighbor
  - the increased number of features invokes the 'cures of dimensionality'. This means that the density of features is decreased, which leads to worse generalization performance.
- Support Vector Machines
  - 1.2(b) has shown that SVM is highly dependent on the kernel function. As this has not changed it's n supprising, that the results are also unchangeotd.

3 Assignment 1.3

[ ]:
```
exp3a = pd.read_csv('exp3a.csv')
exp3a.name = 'exp3a'
exp3b = pd.read_csv('exp3b.csv')
exp3b.name = 'exp3b'
exp3c = pd.read_csv('exp3c.csv')
exp3c.name = 'exp3c'
exp3d = pd.read_csv('exp3d.csv')
exp3d.name = 'exp3d'
```

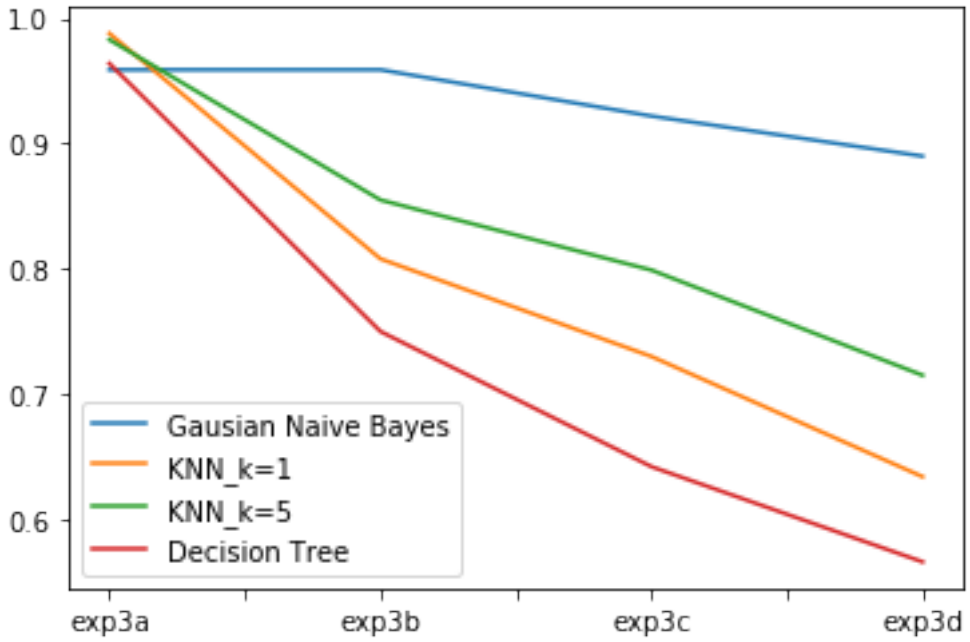
[ ]:
```
des_tree = DecisionTreeClassifier(criterion='entropy')
knn = KNeighborsClassifier()
gau_nav_bay = GaussianNB()
log_reg = LogisticRegression()
svm_clf = SVC(kernel='linear')
```

3.1 (a)

[ ]:
```
idx = ['Gausian Naive Bayes', 'KNN_k=1', 'KNN_k=5', 'Decision Tree']
cols = ['exp3a', 'exp3b', 'exp3c', 'exp3d']
results_1_3_a = pd.DataFrame(index=idx, columns=cols)
for name, clf in zip(['Gausian Naive Bayes', 'KNN_k=1', 'KNN_k=5', 'Decision␣
 ↪Tree'], [GaussianNB(), KNeighborsClassifier(n_neighbors=1),␣
 ↪KNeighborsClassifier(n_neighbors=5),␣
 ↪DecisionTreeClassifier(criterion='entropy')]):
    for exp in [exp3a, exp3b, exp3c, exp3d]:
        X = exp.iloc[:,:-1]
        y = exp.iloc[:,-1]
        y_predict = cross_val_predict(clf, X, y, cv=10, n_jobs=-1)
        acc = accuracy_score(y, y_predict)
        results_1_3_a.loc[name, exp.name] = acc
results_1_3_a.T.plot.line()
results_1_3_a
```

[ ]:

	exp3a	exp3b	exp3c	exp3d
Gausian Naive Bayes	0.959	0.959	0.922	0.89
KNN_k=1	0.988	0.808	0.73	0.634
KNN_k=5	0.983	0.855	0.799	0.715
Decision Tree	0.964	0.75	0.642	0.566



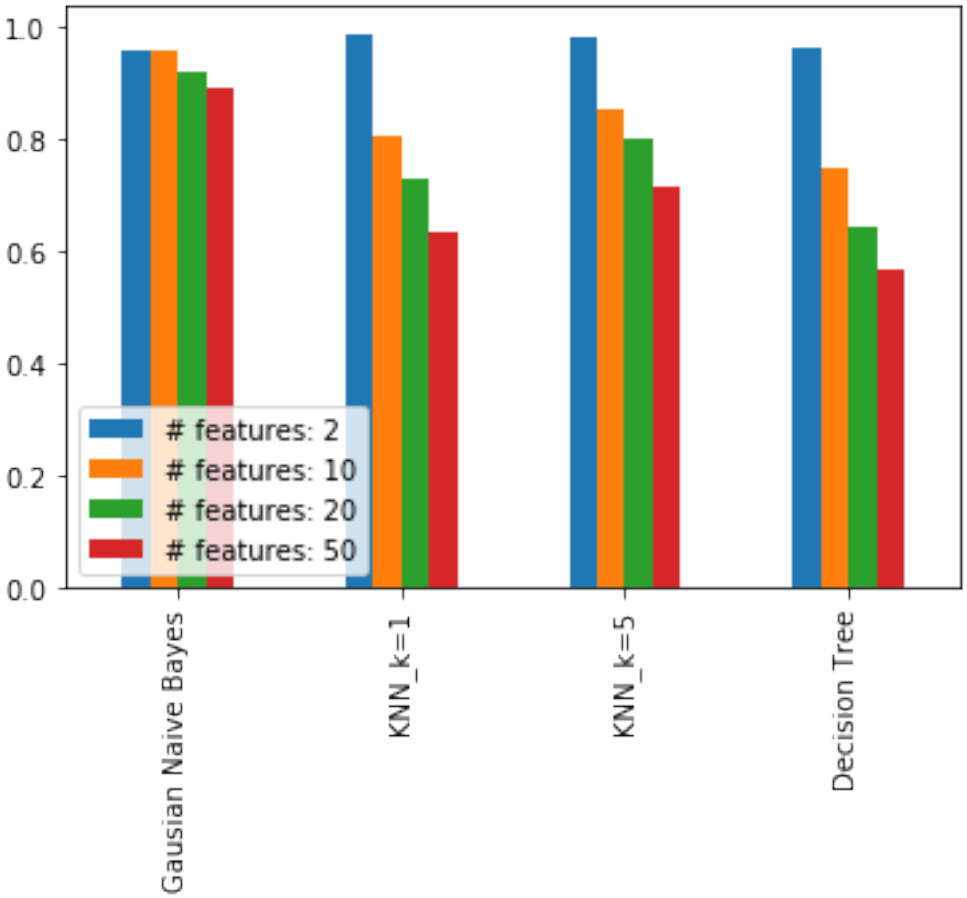
We can see that all classifiers have the highest accuracy for exp3a and the lowest for exp3d.

3.2 (b)

[ ]:
```
results_1_3_a.plot.bar()
plt.legend(labels = [f'# features: {exp.iloc[:,:-1].shape[1]}' for exp in␣
 ↪[exp3a, exp3b, exp3c, exp3d]], loc=3)
results_1_3_a.columns = [f'# features: {exp.iloc[:,:-1].shape[1]}' for exp in␣
 ↪[exp3a, exp3b, exp3c, exp3d]]
results_1_3_a
```

[ ]:

	# features: 2	# features: 10	# features: 20	# features: 50
Gausian Naive Bayes	0.959	0.959	0.922	0.89
KNN_k=1	0.988	0.808	0.73	0.634
KNN_k=5	0.983	0.855	0.799	0.715
Decision Tree	0.964	0.75	0.642	0.566



To evaluate this correclty we have to take into account that the number of features increases from exp3a to exp3d. As we can clearly see the increase of features leads to an decrease in accuracy. This effect is of different strength for different classifiers. The best performing classifier is Gausian Naive Bayes, which only decreases from 0.959 for 2 features to 0.89 for 50 features. k-NearestNeighbors on the other hand perform worse for increasing numbers of features. This can be very well explained with the curse of dimensionality. This describes the fact that data is less dense the more dimensions are taken into account. It's noteworthy however, that a smaller k (k=1) performs better for low dimensions than a higher k (k=5). For higher dimensions however this effect is reversed. So KNN_k=1 declines from 0.988 to 0.634, whereas the KNN_k=5 starts lower at 0.983, but ends higher at 0.715. The decision tree sees the highest drop in accuracy (from 0.966 to 0.554). This can be explained with the fact, that the data is distributed in a way, that's very hard to capture for a decision tree. For higher dimensions this effect increases, meaning that the individual decision trees are heavily overfitted, so they don't generalize very well.