Mud card answers

- **why we change the confusion matrix to get condition negative and condition positive to have 90% of accuracy?**
  - the confusion matrix didn't change, we just normalize it differently
- **We are going to learn AB testing next class?**
  - we will cover a bit of that after the thanksgiving break
  - AB testing is also known as hypothesis testing and you'll cover more of that in data2020
- **Actually I can't find the sample_weight in XGbosst. Also I plug it in params and the RMSE does not change. I find a similar name that "sample_type: weighted. " Is that the class weight in xgb?**
  - search for 'sample_weight' in the python api here
  - I'm not sure what values you tried with sample_weight but RMSE is a regression metric, sample weight is most useful in imbalanced classification
- **Can you please explain one more time how it works when all features in test set are all missing?**
  - I recommend you read through the two papers I linked
  - you can still train models if you have other features that are complete
  - e.g., in the kaggle house price dataset, three features contain missing values and 218 features are complete
  - even if all three features are missing, you can still use the other 218 features
- **a bit confused on when to apply reduced features vs XGB**
  - when you work with missing data, you'll likely want to try both
- **For the accuracy example you showed in class, the deployed model had an accuracy below the baseline. Is this always the case? I have nothing other than intuition telling me that it should be at least at baseline some of the time, but I don't necessarily see how.**
  - accuracy can be under the baseline but such models are not useful

Global feature importance metrics

By the end of this module, you will be able to

- perform permutation feature importance calculation
- study the coefficients of linear models
- outlook to other metrics

The supervised ML pipeline

The goal: Use the training data (X and y) to develop a model which can accurately predict the target variable (y_new') for previously unseen data (X_new).

1. Exploratory Data Analysis (EDA): you need to understand your data and verify that it doesn't contain errors

- do as much EDA as you can!

2. Split the data into different sets: most often the sets are train, validation, and test (or holdout)

- practitioners often make errors in this step!
- you can split the data randomly, based on groups, based on time, or any other non-standard way if necessary to answer your ML question

3. Preprocess the data: ML models only work if X and Y are numbers! Some ML models additionally require each feature to have 0 mean and 1 standard deviation (standardized features)

- often the original features you get contain strings (for example a gender feature would contain 'male', 'female', 'non-binary', 'unknown') which needs to transformed into numbers
- often the features are not standardized (e.g., age is between 0 and 100) but it needs to be standardized

4. Choose an evaluation metric: depends on the priorities of the stakeholders

- often requires quite a bit of thinking and ethical considerations

5. Choose one or more ML techniques: it is highly recommended that you try multiple models

- start with simple models like linear or logistic regression
- try also more complex models like nearest neighbors, support vector machines, random forest, etc.

6. Tune the hyperparameters of your ML models (aka cross-validation)

- ML techniques have hyperparameters that you need to optimize to achieve best performance
- for each ML model, decide which parameters to tune and what values to try
- loop through each parameter combination
  - train one model for each parameter combination
  - evaluate how well the model performs on the validation set
- take the parameter combo that gives the best validation score
- evaluate that model on the test set to report how well the model is expected to perform on previously unseen data

7. Interpret your model: black boxes are often not useful

- check if your model uses features that make sense (excellent tool for debugging)
- often model predictions are not enough, you need to be able to explain how the model arrived to a particular prediction (e.g., in health care)

Motivation

- debugging ML models is tough
    - a model that runs without errors/warning is not necessarily correct
- how do you know that you model is correct?
    - check test set predictions
        - in regression: check points with a large difference between true and predicted values
        - in classification: confusion matrix, check out FPs and FNs
    - inspect your model
        - especially useful for non-linear models
        - metrics to measure how much a model depends on a feature is one way to inspect your model

Global feature importance metrics

By the end of this module, you will be able to

- **perform permutation feature importance calculation**
- study coefficients of linear models
- outlook to other metrics

Permutation feature importance

- model agnostic, you can use it with any supervised ML model
- steps:
    - train a model and calculate a test score :)
    - randomly shuffle a single feature in the test set
    - recalculate the test score with the shuffled data
    - model score worsens because the shuffling breaks the relationship between feature and target
    - the larger the difference, the more important the feature is

In [1]:

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.svm import SVC
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedKFold
from sklearn.preprocessing import StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder
import matplotlib.pylab as plt

df = pd.read_csv('data/adult_data.csv')
label = 'gross-income'
```

```
y = LabelEncoder().fit_transform(df[label])
df.drop(columns=[label],inplace=True)
X = df
ftr_names = X.columns
print(X.head())
print(y)
```

```
   age          workclass  fnlwgt  education  education-num  \
0   39          State-gov   77516  Bachelors             13
1   50   Self-emp-not-inc   83311  Bachelors             13
2   38            Private  215646    HS-grad              9
3   53            Private  234721       11th              7
4   28            Private  338409  Bachelors             13

        marital-status         occupation   relationship   race     sex  \
0        Never-married       Adm-clerical  Not-in-family  White    Male
1   Married-civ-spouse    Exec-managerial        Husband  White    Male
2             Divorced  Handlers-cleaners  Not-in-family  White    Male
3   Married-civ-spouse  Handlers-cleaners        Husband  Black    Male
4   Married-civ-spouse     Prof-specialty           Wife  Black  Female

   capital-gain  capital-loss  hours-per-week  native-country
0          2174             0              40   United-States
1             0             0              13   United-States
2             0             0              40   United-States
3             0             0              40   United-States
4             0             0              40            Cuba
[0 0 0 ... 0 0 1]
```

In [2]:

```
def ML_pipeline_kfold(X,y,random_state,n_folds):
    # create a test set
    X_other, X_test, y_other, y_test = train_test_split(X, y, test_size=0.2, ran
    # splitter for _other
    kf = StratifiedKFold(n_splits=n_folds,shuffle=True,random_state=random_state
    # create the pipeline: preprocessor + supervised ML method
    cat_ftrs = ['workclass','education','marital-status','occupation','relations
    cont_ftrs = ['age','fnlwgt','education-num','capital-gain','capital-loss','h
    # one-hot encoder
    categorical_transformer = Pipeline(steps=[
        ('onehot', OneHotEncoder(sparse=False,handle_unknown='ignore'))])
    # standard scaler
    numeric_transformer = Pipeline(steps=[
        ('scaler', StandardScaler())])
    preprocessor = ColumnTransformer(
        transformers=[
            ('num', numeric_transformer, cont_ftrs),
            ('cat', categorical_transformer, cat_ftrs)])
    pipe = make_pipeline(preprocessor,SVC())
    # the parameter(s) we want to tune
    param_grid = {'svc__C': [0.01, 0.1, 1, 10, 100],
                  'svc__gamma': [0.01, 0.1, 1, 10, 100]}
    # prepare gridsearch
    grid = GridSearchCV(pipe, param_grid=param_grid,cv=kf, return_train_score =
    # do kfold CV on _other
    grid.fit(X_other, y_other)
    return grid, X_test, y_test
```

Be careful, SVM is used on a relatively large dataset

In [3]:
```python
grid, X_test, y_test = ML_pipeline_kfold(X,y,42,4)
print(grid.best_score_)
print(grid.score(X_test,y_test))
print(grid.best_params_)

# save the output so I can use it later
import pickle
file = open('results/grid.save', 'wb')
pickle.dump((grid,X_test,y_test),file)
file.close()
```

```
Fitting 4 folds for each of 25 candidates, totalling 100 fits
[CV 2/4; 2/25] START svc__C=0.01, svc__gamma=0.1................................
[CV 2/4; 2/25] END svc__C=0.01, svc__gamma=0.1;, score=(train=0.822, test=0.814)
total time= 1.5min
[CV 1/4; 4/25] START svc__C=0.01, svc__gamma=10.................................
[CV 1/4; 4/25] END svc__C=0.01, svc__gamma=10;, score=(train=0.759, test=0.759)
total time= 4.4min
[CV 3/4; 6/25] START svc__C=0.1, svc__gamma=0.01................................
[CV 3/4; 6/25] END svc__C=0.1, svc__gamma=0.01;, score=(train=0.843, test=0.844)
total time= 1.2min
[CV 3/4; 7/25] START svc__C=0.1, svc__gamma=0.1.................................
[CV 3/4; 7/25] END svc__C=0.1, svc__gamma=0.1;, score=(train=0.852, test=0.853)
total time=  58.2s
[CV 3/4; 8/25] START svc__C=0.1, svc__gamma=1...................................
[CV 3/4; 8/25] END svc__C=0.1, svc__gamma=1;, score=(train=0.779, test=0.772) to
tal time= 4.4min
[CV 1/4; 10/25] START svc__C=0.1, svc__gamma=100................................
[CV 1/4; 10/25] END svc__C=0.1, svc__gamma=100;, score=(train=0.759, test=0.759)
total time= 5.2min
[CV 1/4; 14/25] START svc__C=1, svc__gamma=10...................................
[CV 1/4; 14/25] END svc__C=1, svc__gamma=10;, score=(train=0.980, test=0.765) to
tal time= 6.0min
[CV 1/4; 16/25] START svc__C=10, svc__gamma=0.01................................
[CV 1/4; 16/25] END svc__C=10, svc__gamma=0.01;, score=(train=0.859, test=0.854)
total time= 1.0min
[CV 2/4; 17/25] START svc__C=10, svc__gamma=0.1.................................
[CV 2/4; 17/25] END svc__C=10, svc__gamma=0.1;, score=(train=0.907, test=0.846)
total time= 1.8min
[CV 3/4; 18/25] START svc__C=10, svc__gamma=1...................................
[CV 3/4; 18/25] END svc__C=10, svc__gamma=1;, score=(train=0.972, test=0.800) to
tal time= 6.7min
[CV 1/4; 20/25] START svc__C=10, svc__gamma=100.................................
[CV 1/4; 20/25] END svc__C=10, svc__gamma=100;, score=(train=0.999, test=0.758)
total time= 7.5min
[CV 1/4; 24/25] START svc__C=100, svc__gamma=10.................................
[CV 1/4; 24/25] END svc__C=100, svc__gamma=10;, score=(train=0.998, test=0.760)
total time= 6.4min
[CV 3/4; 2/25] START svc__C=0.01, svc__gamma=0.1................................
[CV 3/4; 2/25] END svc__C=0.01, svc__gamma=0.1;, score=(train=0.817, test=0.818)
total time= 1.5min
[CV 2/4; 4/25] START svc__C=0.01, svc__gamma=10.................................
[CV 2/4; 4/25] END svc__C=0.01, svc__gamma=10;, score=(train=0.759, test=0.759)
total time= 4.3min
[CV 2/4; 6/25] START svc__C=0.1, svc__gamma=0.01................................
[CV 2/4; 6/25] END svc__C=0.1, svc__gamma=0.01;, score=(train=0.845, test=0.838)
total time= 1.2min
[CV 1/4; 7/25] START svc__C=0.1, svc__gamma=0.1.................................
[CV 1/4; 7/25] END svc__C=0.1, svc__gamma=0.1;, score=(train=0.854, test=0.851)
total time=  56.8s
[CV 1/4; 8/25] START svc__C=0.1, svc__gamma=1...................................
```

```
[CV 1/4; 8/25] END svc__C=0.1, svc__gamma=1;, score=(train=0.777, test=0.773) to
tal time= 4.8min
[CV 2/4; 10/25] START svc__C=0.1, svc__gamma=100................................
[CV 2/4; 10/25] END svc__C=0.1, svc__gamma=100;, score=(train=0.759, test=0.759)
total time= 5.1min
[CV 2/4; 14/25] START svc__C=1, svc__gamma=10...................................
[CV 2/4; 14/25] END svc__C=1, svc__gamma=10;, score=(train=0.980, test=0.766) to
tal time= 6.0min
[CV 3/4; 16/25] START svc__C=10, svc__gamma=0.01................................
[CV 3/4; 16/25] END svc__C=10, svc__gamma=0.01;, score=(train=0.859, test=0.856)
total time= 1.0min
[CV 3/4; 17/25] START svc__C=10, svc__gamma=0.1.................................
[CV 3/4; 17/25] END svc__C=10, svc__gamma=0.1;, score=(train=0.908, test=0.846)
total time= 1.8min
[CV 4/4; 18/25] START svc__C=10, svc__gamma=1...................................
[CV 4/4; 18/25] END svc__C=10, svc__gamma=1;, score=(train=0.973, test=0.794) to
tal time= 7.2min
[CV 3/4; 20/25] START svc__C=10, svc__gamma=100.................................
[CV 3/4; 20/25] END svc__C=10, svc__gamma=100;, score=(train=0.999, test=0.760)
total time= 7.4min
[CV 3/4; 24/25] START svc__C=100, svc__gamma=10.................................
[CV 3/4; 24/25] END svc__C=100, svc__gamma=10;, score=(train=0.998, test=0.760)
total time= 6.2min
0.8545377764127764
[CV 2/4; 1/25] START svc__C=0.01, svc__gamma=0.01...............................
[CV 2/4; 1/25] END svc__C=0.01, svc__gamma=0.01;, score=(train=0.775, test=0.77
5) total time= 1.5min
[CV 3/4; 4/25] START svc__C=0.01, svc__gamma=10.................................
[CV 3/4; 4/25] END svc__C=0.01, svc__gamma=10;, score=(train=0.759, test=0.759)
total time= 4.3min
[CV 1/4; 6/25] START svc__C=0.1, svc__gamma=0.01................................
[CV 1/4; 6/25] END svc__C=0.1, svc__gamma=0.01;, score=(train=0.845, test=0.844)
total time= 1.2min
[CV 2/4; 7/25] START svc__C=0.1, svc__gamma=0.1.................................
[CV 2/4; 7/25] END svc__C=0.1, svc__gamma=0.1;, score=(train=0.854, test=0.844)
total time=  56.2s
[CV 2/4; 8/25] START svc__C=0.1, svc__gamma=1...................................
[CV 2/4; 8/25] END svc__C=0.1, svc__gamma=1;, score=(train=0.778, test=0.775) to
tal time= 4.8min
[CV 4/4; 10/25] START svc__C=0.1, svc__gamma=100................................
[CV 4/4; 10/25] END svc__C=0.1, svc__gamma=100;, score=(train=0.759, test=0.759)
total time= 5.1min
[CV 3/4; 14/25] START svc__C=1, svc__gamma=10...................................
[CV 3/4; 14/25] END svc__C=1, svc__gamma=10;, score=(train=0.981, test=0.768) to
tal time= 6.0min
[CV 4/4; 16/25] START svc__C=10, svc__gamma=0.01................................
[CV 4/4; 16/25] END svc__C=10, svc__gamma=0.01;, score=(train=0.858, test=0.854)
total time= 1.1min
[CV 4/4; 17/25] START svc__C=10, svc__gamma=0.1.................................
[CV 4/4; 17/25] END svc__C=10, svc__gamma=0.1;, score=(train=0.906, test=0.849)
total time= 1.5min
[CV 2/4; 18/25] START svc__C=10, svc__gamma=1...................................
[CV 2/4; 18/25] END svc__C=10, svc__gamma=1;, score=(train=0.971, test=0.803) to
tal time= 7.2min
[CV 2/4; 20/25] START svc__C=10, svc__gamma=100.................................
[CV 2/4; 20/25] END svc__C=10, svc__gamma=100;, score=(train=0.999, test=0.760)
total time= 7.4min
[CV 2/4; 24/25] START svc__C=100, svc__gamma=10.................................
[CV 2/4; 24/25] END svc__C=100, svc__gamma=10;, score=(train=0.998, test=0.768)
total time= 6.4min
[CV 1/4; 1/25] START svc__C=0.01, svc__gamma=0.01...............................
```

```
[CV 1/4; 1/25] END svc__C=0.01, svc__gamma=0.01;, score=(train=0.769, test=0.77
1) total time= 1.5min
[CV 4/4; 4/25] START svc__C=0.01, svc__gamma=10.................................
[CV 4/4; 4/25] END svc__C=0.01, svc__gamma=10;, score=(train=0.759, test=0.759)
total time= 4.3min
[CV 4/4; 6/25] START svc__C=0.1, svc__gamma=0.01................................
[CV 4/4; 6/25] END svc__C=0.1, svc__gamma=0.01;, score=(train=0.844, test=0.844)
total time= 1.2min
[CV 4/4; 7/25] START svc__C=0.1, svc__gamma=0.1.................................
[CV 4/4; 7/25] END svc__C=0.1, svc__gamma=0.1;, score=(train=0.853, test=0.851)
total time=  59.0s
[CV 4/4; 8/25] START svc__C=0.1, svc__gamma=1...................................
[CV 4/4; 8/25] END svc__C=0.1, svc__gamma=1;, score=(train=0.775, test=0.775) to
tal time= 4.4min
[CV 3/4; 10/25] START svc__C=0.1, svc__gamma=100................................
[CV 3/4; 10/25] END svc__C=0.1, svc__gamma=100;, score=(train=0.759, test=0.759)
total time= 5.3min
[CV 4/4; 14/25] START svc__C=1, svc__gamma=10...................................
[CV 4/4; 14/25] END svc__C=1, svc__gamma=10;, score=(train=0.981, test=0.766) to
tal time= 5.9min
[CV 2/4; 16/25] START svc__C=10, svc__gamma=0.01................................
[CV 2/4; 16/25] END svc__C=10, svc__gamma=0.01;, score=(train=0.861, test=0.848)
total time=  59.8s
[CV 1/4; 17/25] START svc__C=10, svc__gamma=0.1.................................
[CV 1/4; 17/25] END svc__C=10, svc__gamma=0.1;, score=(train=0.905, test=0.853)
total time= 1.5min
[CV 1/4; 18/25] START svc__C=10, svc__gamma=1...................................
[CV 1/4; 18/25] END svc__C=10, svc__gamma=1;, score=(train=0.971, test=0.798) to
tal time= 7.4min
[CV 4/4; 20/25] START svc__C=10, svc__gamma=100.................................
[CV 4/4; 20/25] END svc__C=10, svc__gamma=100;, score=(train=0.999, test=0.760)
total time= 7.4min
[CV 4/4; 24/25] START svc__C=100, svc__gamma=10.................................
[CV 4/4; 24/25] END svc__C=100, svc__gamma=10;, score=(train=0.998, test=0.760)
total time= 6.3min
0.8624289881774911
{'svc__C': 1, 'svc__gamma': 0.1}
```

In [5]:

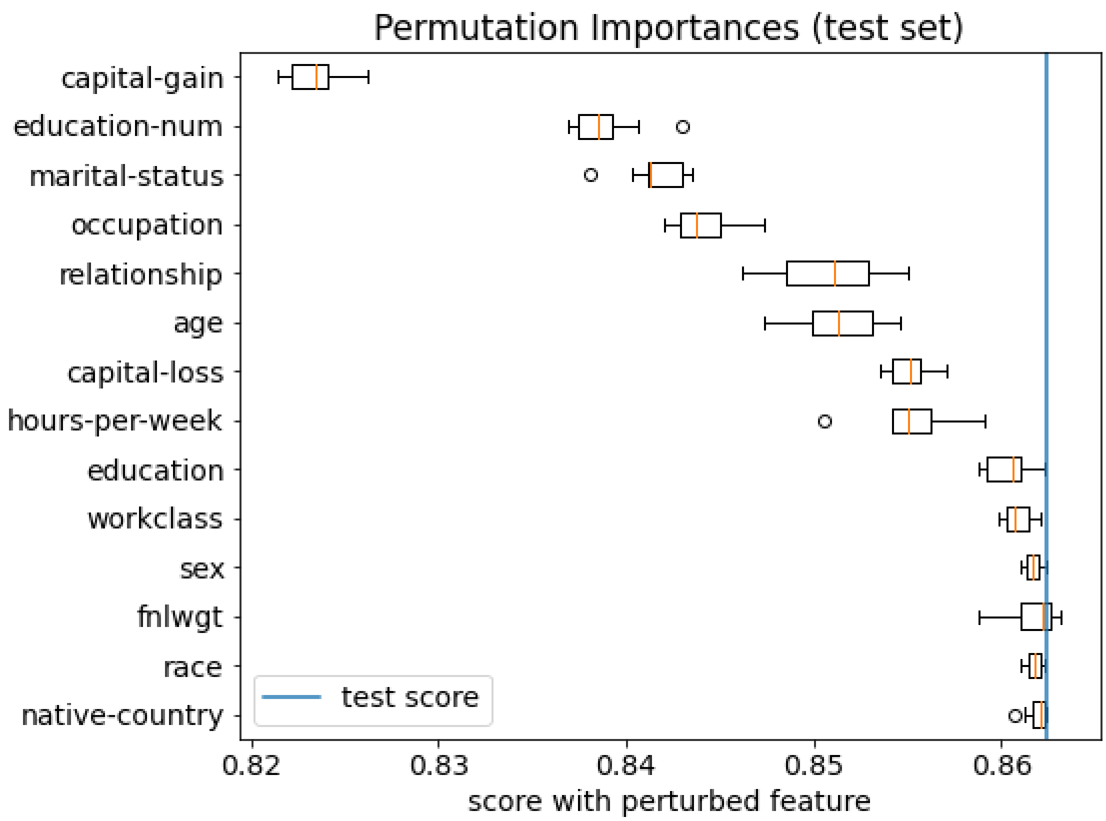
```python
import pickle
file = open('results/grid.save', 'rb')
grid, X_test, y_test = pickle.load(file)
file.close()

np.random.seed(42)

nr_runs = 10
scores = np.zeros([len(ftr_names),nr_runs])

test_score = grid.score(X_test,y_test)
print('test score = ',test_score)
print('test baseline = ',np.sum(y_test == 0)/len(y_test))
# loop through the features
for i in range(len(ftr_names)):
    print('shuffling '+str(ftr_names[i]))
    acc_scores = []
    for j in range(nr_runs):
        X_test_shuffled = X_test.copy()
        X_test_shuffled[ftr_names[i]] = np.random.permutation(X_test[ftr_names[i
        acc_scores.append(grid.score(X_test_shuffled,y_test))
```

```python
    print('   shuffled test score:',np.around(np.mean(acc_scores),3),'+/-',np.ar
    scores[i] = acc_scores
```

```
test score =  0.8624289881774911
test baseline =  0.7587901120835252
shuffling age
   shuffled test score: 0.851 +/- 0.002
shuffling workclass
   shuffled test score: 0.861 +/- 0.001
shuffling fnlwgt
   shuffled test score: 0.862 +/- 0.001
shuffling education
   shuffled test score: 0.86 +/- 0.001
shuffling education-num
   shuffled test score: 0.839 +/- 0.002
shuffling marital-status
   shuffled test score: 0.842 +/- 0.002
shuffling occupation
   shuffled test score: 0.844 +/- 0.002
shuffling relationship
   shuffled test score: 0.851 +/- 0.003
shuffling race
   shuffled test score: 0.862 +/- 0.0
shuffling sex
   shuffled test score: 0.862 +/- 0.0
shuffling capital-gain
   shuffled test score: 0.823 +/- 0.001
shuffling capital-loss
   shuffled test score: 0.855 +/- 0.001
shuffling hours-per-week
   shuffled test score: 0.855 +/- 0.002
shuffling native-country
   shuffled test score: 0.862 +/- 0.001
```

In [6]:

```python
sorted_indcs = np.argsort(np.mean(scores,axis=1))[::-1]
plt.rcParams.update({'font.size': 14})
plt.figure(figsize=(8,6))
plt.boxplot(scores[sorted_indcs].T,labels=ftr_names[sorted_indcs],vert=False)
plt.axvline(test_score,label='test score')
plt.title("Permutation Importances (test set)")
plt.xlabel('score with perturbed feature')
plt.legend()
plt.tight_layout()
plt.show()
```



Check out sklearn's permutation importance!

https://scikit-learn.org/stable/modules/generated/sklearn.inspection.permutation_importance.html

https://scikit-learn.org/stable/modules/permutation_importance.html#permutation-importance

Cons of permutation feature importance

- strongly correlated features
    - if one of the features is shuffled, the model can still use the other correlated feature
    - both features appear to be less important but they might actually be important
    - solution:
        - check the correlation matrix plot
        - remove all but one of the strongly correlated features
- no feature interactions
    - one feature might appear unimportant but combined with another feature could be important
    - solution:
        - permute two features to measure how important feature pairs are
        - this can be computationally expensive

Quiz

Global feature importance metrics

By the end of this module, you will be able to

- perform permutation feature importance calculation
- **study the coefficients of linear models**
- outlook to other metrics

Coefficients of linear models

- the coefficients of linear and logistic regression can be used as a measure of feature importance **ONLY IF** all features have a zero mean and the same standard deviation (usually 1)
    - all features meaning that the one-hot encoded and ordinal features as well!
- then the absolute value of the coefficients can be used to rank them

Let's rewrite the kfold CV function a bit

In [11]:

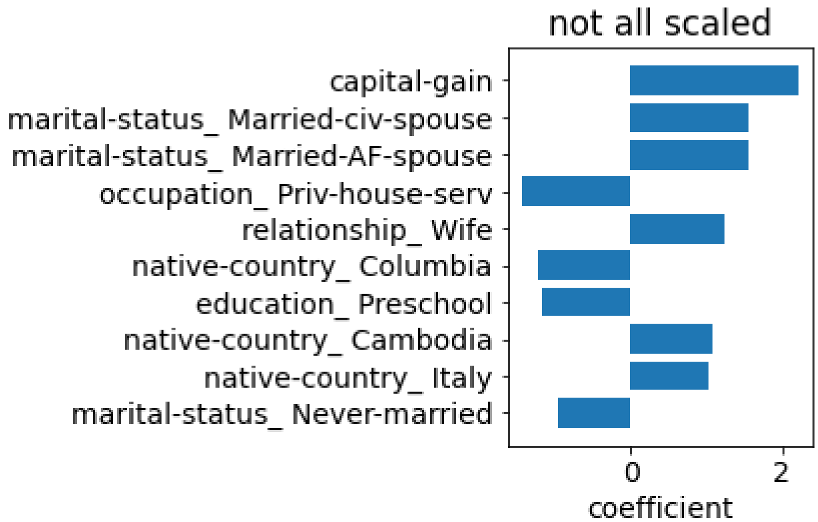
```
from sklearn.linear_model import LogisticRegression
def ML_pipeline_kfold_LR1(X,y,random_state,n_folds):
    # create a test set
    X_other, X_test, y_other, y_test = train_test_split(X, y, test_size=0.2, ran
    # splitter for _other
    kf = StratifiedKFold(n_splits=n_folds,shuffle=True,random_state=random_state
    # create the pipeline: preprocessor + supervised ML method
    cat_ftrs = ['workclass','education','marital-status','occupation','relations
    cont_ftrs = ['age','fnlwgt','education-num','capital-gain','capital-loss','h
    # one-hot encoder
    categorical_transformer = Pipeline(steps=[
        ('onehot', OneHotEncoder(sparse=False,handle_unknown='ignore'))])
    # standard scaler
    numeric_transformer = Pipeline(steps=[
        ('scaler', StandardScaler())])
    preprocessor = ColumnTransformer(
        transformers=[
            ('num', numeric_transformer, cont_ftrs),
            ('cat', categorical_transformer, cat_ftrs)])
    pipe = make_pipeline(preprocessor,LogisticRegression(penalty='l2',solver='lb
    # the parameter(s) we want to tune
    param_grid = {'logisticregression__C': [0.01, 0.1, 1, 10,100]}
    # prepare gridsearch
    grid = GridSearchCV(pipe, param_grid=param_grid,cv=kf, return_train_score =
    # do kfold CV on _other
    grid.fit(X_other, y_other)
    feature_names = cont_ftrs + \
                list(grid.best_estimator_[0].named_transformers_['cat'][0].get_f
    return grid, np.array(feature_names), X_test, y_test
```

In [12]:

```
grid, feature_names, X_test, y_test = ML_pipeline_kfold_LR1(X,y,42,4)
print('test score:',grid.score(X_test,y_test))
coefs = grid.best_estimator_[-1].coef_[0]
sorted_indcs = np.argsort(np.abs(coefs))
```

```
plt.rcParams.update({'font.size': 14})
plt.barh(np.arange(10),coefs[sorted_indcs[-10:]])
plt.yticks(np.arange(10),feature_names[sorted_indcs[-10:]])
plt.xlabel('coefficient')
plt.title('not all scaled')
plt.tight_layout()
plt.savefig('figures/LR_coefs_notscaled.png',dpi=300)
plt.show()
```

```
test score: 0.8582834331337326
```

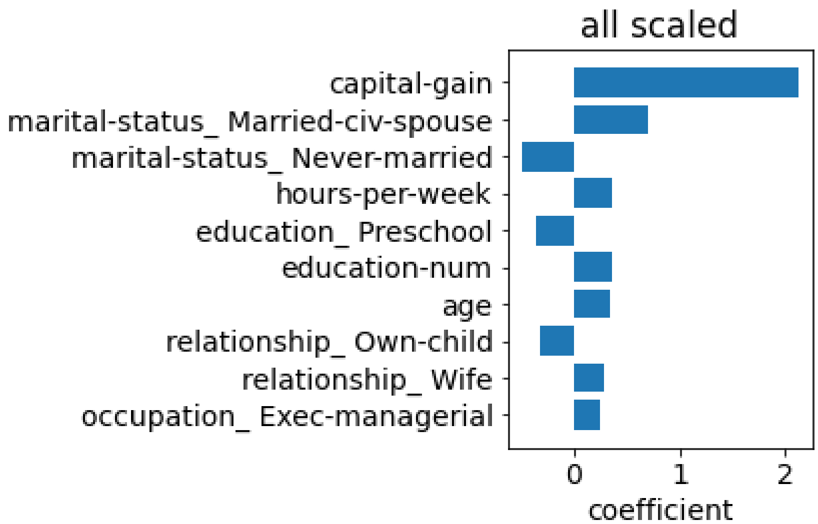


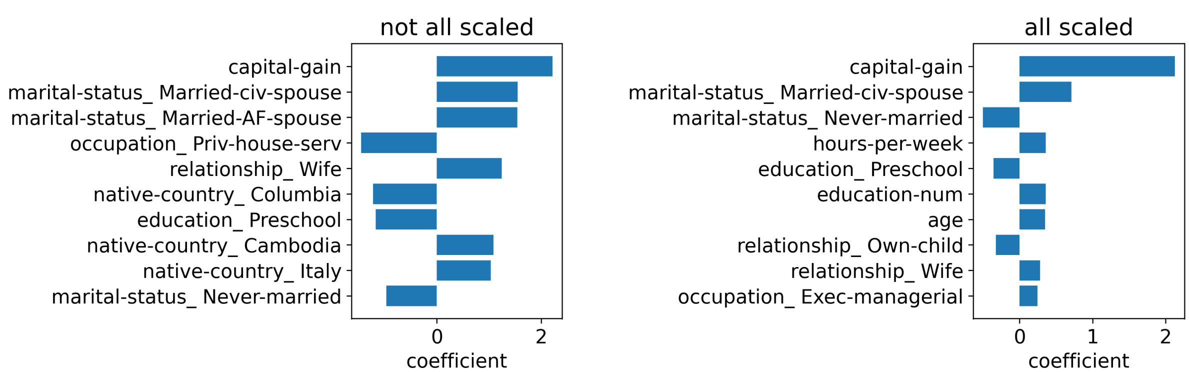
In [13]:

```
from sklearn.linear_model import LogisticRegression
def ML_pipeline_kfold_LR2(X,y,random_state,n_folds):
    # create a test set
    X_other, X_test, y_other, y_test = train_test_split(X, y, test_size=0.2, ran
    # splitter for _other
    kf = StratifiedKFold(n_splits=n_folds,shuffle=True,random_state=random_state
    # create the pipeline: preprocessor + supervised ML method
    cat_ftrs = ['workclass','education','marital-status','occupation','relations
    cont_ftrs = ['age','fnlwgt','education-num','capital-gain','capital-loss','h
    # one-hot encoder
    categorical_transformer = Pipeline(steps=[
        ('onehot', OneHotEncoder(sparse=False,handle_unknown='ignore'))])
    # standard scaler
    numeric_transformer = Pipeline(steps=[
        ('scaler', StandardScaler())])
    preprocessor = ColumnTransformer(
        transformers=[
            ('num', numeric_transformer, cont_ftrs),
            ('cat', categorical_transformer, cat_ftrs)])
    final_scaler = StandardScaler()
    pipe = make_pipeline(preprocessor,final_scaler,LogisticRegression(penalty='l
    # the parameter(s) we want to tune
    param_grid = {'logisticregression__C': [0.01, 0.1, 1, 10,100]}
    # prepare gridsearch
    grid = GridSearchCV(pipe, param_grid=param_grid,cv=kf, return_train_score =
    # do kfold CV on _other
    grid.fit(X_other, y_other)
    feature_names = cont_ftrs + \
                list(grid.best_estimator_[0].named_transformers_['cat'][0].get_f
    return grid, np.array(feature_names), X_test, y_test
```

```
In [14]: grid, feature_names, X_test, y_test = ML_pipeline_kfold_LR2(X,y,42,4)
         print('test score:',grid.score(X_test,y_test))
         coefs = grid.best_estimator_[-1].coef_[0]
         sorted_indcs = np.argsort(np.abs(coefs))

         plt.rcParams.update({'font.size': 14})
         plt.barh(np.arange(10),coefs[sorted_indcs[-10:]])
         plt.yticks(np.arange(10),feature_names[sorted_indcs[-10:]])
         plt.xlabel('coefficient')
         plt.title('all scaled')
         plt.tight_layout()
         plt.savefig('figures/LR_coefs_scaled.png',dpi=300)
         plt.show()
```

```
test score: 0.857976354982343
```





Global feature importance metrics

By the end of this module, you will be able to

- perform permutation feature importance calculation
- study the coefficients of linear models
- **outlook to other metrics**

- SVM:

    - SVC.coef *and SVR.coef* can be used as a metric of feature importance if **all** features are standardized
    - for linear SVMs only!
- random forest:
    - RandomForestRegressor.feature*importances* and RandomForestClassification.feature*importances*
    - gini importance or mean decrease impurity, see here and here
- XGBoost:
    - five different metrics are implemented, see here and here

Quiz

Mudcard

In [ ]:

```

```