ML Posledni Ukol

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7. Zaver

Priprava dat

In [1]:
```
import numpy as np
import pandas as pd
```

In [2]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, ca
ll drive.mount("/content/drive", force_remount=True).
```

In [3]:
```
data =
pd.read_csv("/content/drive/MyDrive/Colab Notebooks/Workshop/Clean_Dataset.c
```

In [4]:
```
data
```

Out[4]:

	Unnamed: 0	airline	flight	source_city	departure_time	stops	arrival_time	des
0	0	SpiceJet	SG-8709	Delhi	Evening	zero	Night	
1	1	SpiceJet	SG-8157	Delhi	Early_Morning	zero	Morning	
2	2	AirAsia	I5-764	Delhi	Early_Morning	zero	Early_Morning	
3	3	Vistara	UK-995	Delhi	Morning	zero	Afternoon	
4	4	Vistara	UK-963	Delhi	Morning	zero	Morning	
...	...	...	...	...	...	...	...	
300148	300148	Vistara	UK-822	Chennai	Morning	one	Evening	
300149	300149	Vistara	UK-826	Chennai	Afternoon	one	Night	
300150	300150	Vistara	UK-832	Chennai	Early_Morning	one	Night	
300151	300151	Vistara	UK-828	Chennai	Early_Morning	one	Evening	
300152	300152	Vistara	UK-822	Chennai	Morning	one	Evening	

300153 rows × 12 columns

In [5]:

```
# vyber pouze radku business tridy
business = data.loc[data['class'] == "Business"]
```

In [6]:

```
business.shape
```

Out[6]: (93487, 12)

In [7]:

```
business
```

Out[7]:

	Unnamed: 0	airline	flight	source_city	departure_time	stops	arrival_time	desti
206666	206666	Air_India	AI-868	Delhi	Evening	zero	Evening	
206667	206667	Air_India	AI-624	Delhi	Evening	zero	Night	
206668	206668	Air_India	AI-531	Delhi	Evening	one	Night	
206669	206669	Air_India	AI-839	Delhi	Night	one	Night	
206670	206670	Air_India	AI-544	Delhi	Evening	one	Night	
...	...	...	...	...	...	...	...	
300148	300148	Vistara	UK-822	Chennai	Morning	one	Evening	
300149	300149	Vistara	UK-826	Chennai	Afternoon	one	Night	
300150	300150	Vistara	UK-832	Chennai	Early_Morning	one	Night	
300151	300151	Vistara	UK-828	Chennai	Early_Morning	one	Evening	
300152	300152	Vistara	UK-822	Chennai	Morning	one	Evening	

93487 rows × 12 columns

In [8]:

```
# odebrani zbytecnych sloupcu
business = business.drop('Unnamed: 0', axis=1)
business = business.drop('class', axis=1)
```

In [9]:

```
business
```

Out[9]:

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city
206666	Air_India	AI-868	Delhi	Evening	zero	Evening	Mumbai
206667	Air_India	AI-624	Delhi	Evening	zero	Night	Mumbai
206668	Air_India	AI-531	Delhi	Evening	one	Night	Mumbai
206669	Air_India	AI-839	Delhi	Night	one	Night	Mumbai
206670	Air_India	AI-544	Delhi	Evening	one	Night	Mumbai
...	...	...	...	...	...	...	...
300148	Vistara	UK-822	Chennai	Morning	one	Evening	Hyderabad
300149	Vistara	UK-826	Chennai	Afternoon	one	Night	Hyderabad
300150	Vistara	UK-832	Chennai	Early_Morning	one	Night	Hyderabad
300151	Vistara	UK-828	Chennai	Early_Morning	one	Evening	Hyderabad
300152	Vistara	UK-822	Chennai	Morning	one	Evening	Hyderabad

93487 rows × 10 columns

Kontrola typu a hodnot promennych

In [10]:
```
business.dtypes
```

Out[10]:
```
airline              object
flight               object
source_city          object
departure_time       object
stops                object
arrival_time         object
destination_city     object
duration            float64
days_left             int64
price                 int64
dtype: object
```

In [11]:
```
business.departure_time.unique()
```

Out[11]:
```
array(['Evening', 'Night', 'Early_Morning', 'Morning', 'Afternoon',
       'Late_Night'], dtype=object)
```

In [12]:
```
business.stops.unique()
```

Out[12]: array(['zero', 'one', 'two_or_more'], dtype=object)

In [13]:
```
business.arrival_time.unique()
```

Out[13]:
```
array(['Evening', 'Night', 'Afternoon', 'Morning', 'Late_Night',
       'Early_Morning'], dtype=object)
```

In [14]:
```
business.source_city.unique()
```

Out[14]:
```
array(['Delhi', 'Mumbai', 'Bangalore', 'Kolkata', 'Hyderabad', 'Chennai'],
      dtype=object)
```

In [15]:
```
business.destination_city.unique()
```

Out[15]:
```
array(['Mumbai', 'Bangalore', 'Kolkata', 'Hyderabad', 'Chennai', 'Delhi'],
      dtype=object)
```

In [16]:
```
business.airline.unique()
```

Out[16]: array(['Air_India', 'Vistara'], dtype=object)

In [17]:
```
business.flight.unique()
```

Out[17]:
```
array(['AI-868', 'AI-624', 'AI-531', 'AI-839', 'AI-544', 'UK-985',
       'AI-479', 'AI-473', 'UK-871', 'UK-977', 'AI-504', 'AI-807',
       'AI-540', 'AI-537', 'UK-817', 'AI-762', 'AI-764', 'UK-707',
       'UK-809', 'UK-813', 'UK-837', 'UK-953', 'AI-887', 'AI-665',
       'AI-805', 'AI-678', 'AI-636', 'AI-441', 'AI-435', 'UK-683',
       'AI-403', 'UK-963', 'UK-955', 'AI-411', 'AI-811', 'AI-453',
       'UK-637', 'UK-927', 'AI-483', 'AI-542', 'AI-560', 'AI-406',
       'UK-829', 'UK-879', 'UK-899', 'UK-627', 'UK-945', 'AI-451',
       'AI-885', 'AI-877', 'UK-995', 'UK-673', 'AI-429', 'UK-859',
       'AI-439', 'UK-839', 'UK-833', 'UK-819', 'UK-801', 'UK-815',
       'UK-706', 'AI-465', 'AI-512', 'AI-767', 'AI-401', 'UK-835',
       'UK-737', 'UK-847', 'UK-951', 'AI-475', 'AI-431', 'UK-933',
       'AI-502', 'AI-506', 'AI-803', 'UK-855', 'UK-705', 'AI-499',
       'AI-471', 'AI-485', 'AI-423', 'AI-415', 'UK-747', 'AI-481',
       'UK-981', 'UK-975', 'UK-993', 'UK-943', 'UK-941', 'UK-811',
       'UK-807', 'AI-837', 'AI-865', 'UK-727', 'AI-491', 'AI-883',
       'AI-437', 'AI-861', 'AI-641', 'UK-812', 'UK-671', 'AI-433',
       'AI-487', 'AI-407', 'AI-889', 'AI-801', 'UK-641', 'AI-895',
       'AI-879', 'AI-489', 'AI-891', 'AI-493', 'AI-888', 'AI-867',
       'AI-631', 'AI-637', 'UK-996', 'UK-940', 'AI-619', 'UK-875',
       'UK-988', 'AI-681', 'AI-774', 'UK-865', 'UK-823', 'AI-806',
       'AI-809', 'AI-687', 'AI-660', 'AI-635', 'AI-442', 'UK-958',
       'UK-928', 'UK-960', 'AI-625', 'UK-613', 'AI-649', 'UK-970',
       'UK-877', 'UK-621', 'UK-944', 'AI-685', 'AI-683', 'AI-669',
       'UK-910', 'UK-651', 'AI-679', 'AI-639', 'AI-570', 'UK-863',
       'UK-851', 'UK-825', 'UK-853', 'AI-671', 'UK-775', 'UK-771',
       'AI-655', 'UK-655', 'AI-645', 'AI-651', 'AI-607', 'AI-673',
       'UK-994', 'AI-643', 'AI-611', 'UK-773', 'UK-954', 'UK-950',
       'UK-902', 'UK-653', 'UK-873', 'UK-986', 'UK-821', 'UK-827',
       'UK-845', 'UK-930', 'UK-849', 'UK-841', 'UK-857', 'AI-864',
       'UK-861', 'AI-615', 'AI-695', 'AI-657', 'AI-633', 'AI-652',
       'AI-629', 'AI-627', 'AI-601', 'AI-623', 'AI-603', 'UK-818',
       'AI-808', 'UK-850', 'UK-808', 'UK-820', 'UK-802', 'AI-505',
       'AI-501', 'AI-804', 'AI-503', 'UK-810', 'AI-507', 'AI-640',
       'UK-657', 'UK-816', 'UK-854', 'UK-852', 'UK-858', 'AI-573',
       'AI-610', 'AI-565', 'UK-867', 'AI-738', 'AI-516', 'AI-523',
       'AI-748', 'UK-866', 'UK-864', 'UK-814', 'UK-846', 'AI-776',
       'AI-604', 'AI-772', 'AI-564', 'AI-583', 'UK-774', 'AI-763',
       'AI-402', 'AI-768', 'AI-770', 'UK-738', 'UK-778', 'AI-729',
       'AI-781', 'AI-526', 'AI-713', 'AI-765', 'AI-773', 'AI-787',
       'UK-776', 'UK-772', 'AI-721', 'UK-720', 'AI-745', 'AI-732',
       'AI-715', 'AI-747', 'AI-424', 'UK-708', 'AI-743', 'AI-780',
       'AI-775', 'AI-771', 'AI-840', 'AI-541', 'UK-860', 'UK-880',
       'UK-830', 'AI-559', 'AI-543', 'UK-890', 'AI-698', 'AI-508',
       'AI-525', 'UK-870', 'UK-876', 'UK-878', 'AI-838', 'AI-515',
       'UK-874', 'AI-616', 'AI-420', 'AI-620', 'AI-546', 'UK-832',
       'UK-838', 'AI-440', 'AI-539', 'AI-538', 'AI-430', 'UK-836',
       'AI-569', 'AI-672', 'AI-766', 'UK-834', 'UK-822', 'AI-549',
       'UK-824', 'UK-828', 'UK-826', 'AI-545', 'AI-551', 'AI-563',
       'AI-509'], dtype=object)
```

One hot encoding promennych

In [18]:
```
transformed = pd.get_dummies(business)
```

In [19]:
```
transformed
```

Out[19]:

	duration	days_left	price	airline_Air_India	airline_Vistara	flight_AI-401	flight_AI-402
206666	2.00	1	25612	1	0	0	0
206667	2.25	1	25612	1	0	0	0
206668	24.75	1	42220	1	0	0	0
206669	26.50	1	44450	1	0	0	0
206670	6.67	1	46690	1	0	0	0
...	...	...	...	...	...	...	...
300148	10.08	49	69265	0	1	0	0
300149	10.42	49	77105	0	1	0	0
300150	13.83	49	79099	0	1	0	0
300151	10.00	49	81585	0	1	0	0
300152	10.08	49	81585	0	1	0	0

93487 rows × 327 columns

In [20]:
```
# Normalizace dat (nakonec nepouzita)
normalized_df =
 (transformed-transformed.min())/(transformed.max()-transformed.min())
```

In [21]:
```
normalized_df
```

Out[21]:

	duration	days_left	price	airline_Air_India	airline_Vistara	flight_AI-401	flight_A 4(
206666	0.021390	0.0	0.122552	1.0	0.0	0.0	0
206667	0.026738	0.0	0.122552	1.0	0.0	0.0	0
206668	0.508021	0.0	0.272078	1.0	0.0	0.0	0
206669	0.545455	0.0	0.292155	1.0	0.0	0.0	0
206670	0.121283	0.0	0.312323	1.0	0.0	0.0	0
...	...	...	...	...	...	...	
300148	0.194225	1.0	0.515571	0.0	1.0	0.0	0
300149	0.201497	1.0	0.586157	0.0	1.0	0.0	0
300150	0.274439	1.0	0.604109	0.0	1.0	0.0	0
300151	0.192513	1.0	0.626491	0.0	1.0	0.0	0
300152	0.194225	1.0	0.626491	0.0	1.0	0.0	0

93487 rows × 327 columns

In [22]:
```
# Rozdeleni na train a test
from sklearn.model_selection import train_test_split
X = np.array(transformed.loc[:, transformed.columns != "price"])
y = np.array(transformed["price"])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,
                                                    random_state = 1)
```

In [23]:
```
X_train
```

Out[23]:
```
array([[19.75, 19.  ,  1.  , ...,  0.  ,  1.  ,  0.  ],
       [12.17,  5.  ,  1.  , ...,  0.  ,  0.  ,  0.  ],
       [22.08, 10.  ,  0.  , ...,  0.  ,  0.  ,  0.  ],
       ...,
       [14.92, 14.  ,  0.  , ...,  1.  ,  0.  ,  0.  ],
       [24.33, 48.  ,  1.  , ...,  0.  ,  0.  ,  1.  ],
       [26.17, 30.  ,  0.  , ...,  0.  ,  1.  ,  0.  ]])
```

In [27]:
```
X_train.shape
```

Out[27]:
```
(74789, 326)
```

In [24]:
```
y_train
```

Out[24]:
```
array([57405, 43729, 57992, ..., 56588, 59033, 58394])
```

Definice ztratove funkce. Vybral jsem si MAPE, primarne pro jeji snadnou interpretovatelnost.

In [25]:
```
def mape(y, yhat):
    return np.mean([np.abs(i-j)/j for i,j in zip(yhat, y)])
```

Referencni jednoducha linearni regrese

In [26]:
```
from sklearn.linear_model import LinearRegression
```

In [27]:
```
linear_regression = LinearRegression()
linear_regression.fit(X_train, y_train)
```

Out[27]:
```
▾ LinearRegression
LinearRegression()
```

In [28]:
```
linear_regression.score(X_test, y_test) # out of sample index determinace
```

Out[28]:
```
-330096676127365.44
```

In [29]:
```
yhat = linear_regression.predict(X_test)
```

In [30]:
```
# mape
mape(y_test, yhat)
```

Out[30]: 58122.98456233965

Dle ocekavani mela uplne nejjednodussi linearni regrese priserne vysledky :D

Elastic net regrese

Elastic net jsem se rozhodl pouzit jelikoz data neznam tak dobre, abych mohl urcit, zda je lepsi L1 nebo L2 regularizace. Jelikoz je vysoky pocet promennych, ocekavam multikolinearitu.

In [31]:
```
from sklearn.linear_model import ElasticNet
```

In [32]:
```
# zakladni model
el = ElasticNet(alpha=1.0, l1_ratio=0.5)

el.fit(X_train, y_train)

mape(y_test, el.predict(X_test))
```

Out[32]: 0.19153055967999336

Uz tenhle vysledek je za me velmi dobry. Prumerna out-of-sample absolutni chyba pod 20% je slusna :D

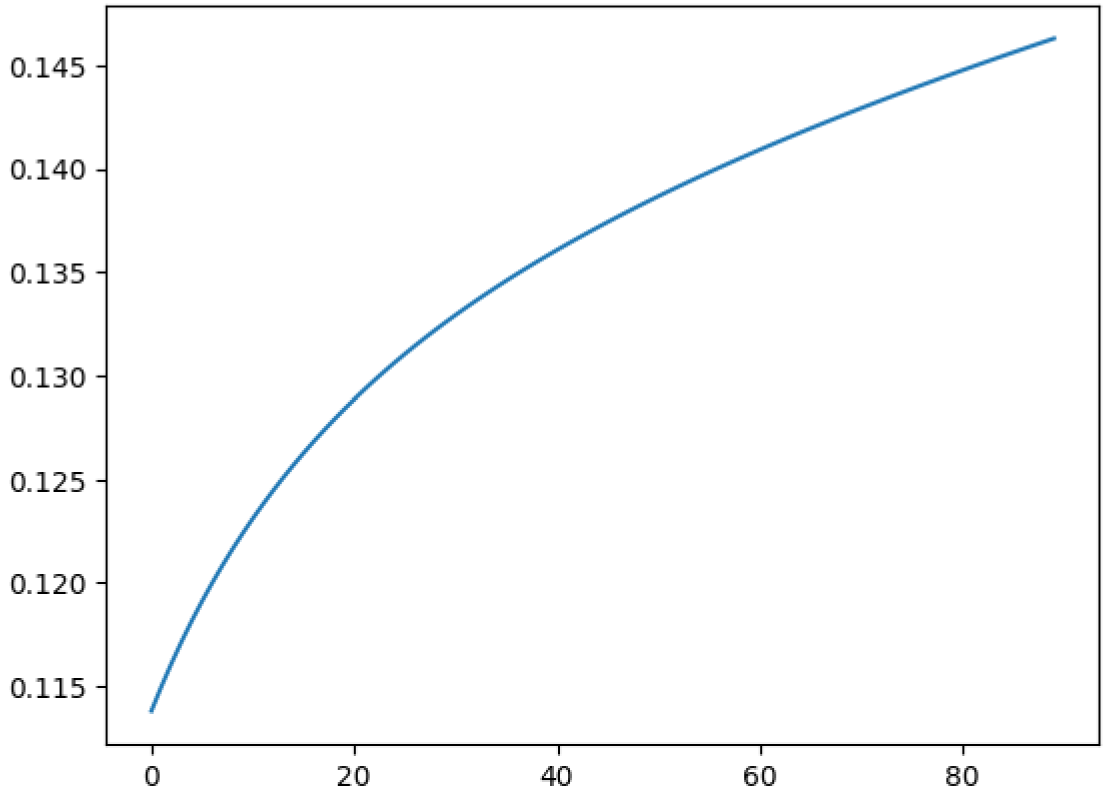
In [33]:
```
# hledani optimalni lambdy/alphy
lambdas = list()
for i in range(1000, 10_000, 100):
    res = ElasticNet(alpha = i/10_000 , l1_ratio=0.95) # 0.95 doplneno zpetn
    res.fit(X_train, y_train)
    lambdas.append(mape(y_train, res.predict(X_train))) # insample mape
```

In [34]:
```
# hledani optimalniho parametru pro volbu L1/L2 regularizace
l1_wts = list()
for i in range(1000, 10_000, 100):
    res = ElasticNet(alpha = 0.1, l1_ratio = i/10000)
    res.fit(X_train, y_train)
    l1_wts.append(mape(y_train, res.predict(X_train)))
```

In [35]:
```
import matplotlib.pyplot as plt
```

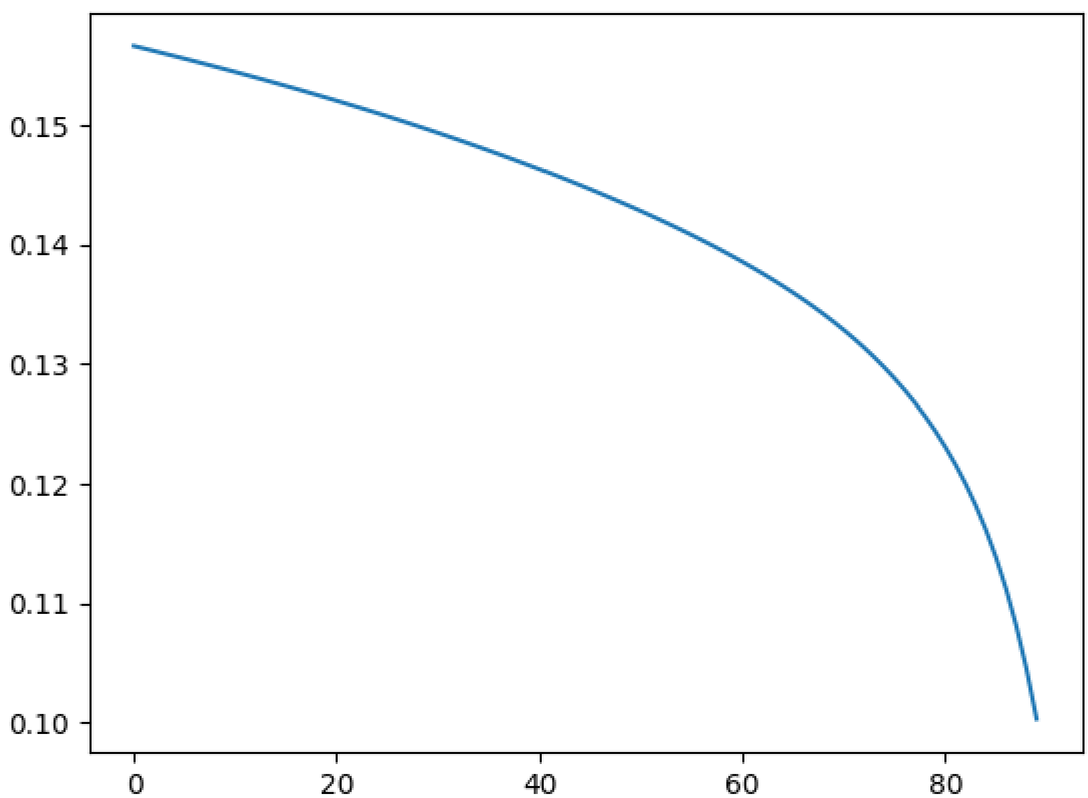
In [36]:
```
plt.plot(range(90), lambdas)
# zda se ze lambda bude velmi mala, asi 0,1
```

Out[36]:
```
[<matplotlib.lines.Line2D at 0x7fb3a0b43820>]
```



In [37]:
```
plt.plot(range(90), l1_wts)
# zda se ze vhodnejsi je lasso regrese (vyssi hodnota lambda)
```

Out[37]: [<matplotlib.lines.Line2D at 0x7fb3a099c4c0>]



Nakonec se jako vhodny model jevi linearni regrese s L1 regularizaci (Lasso), ktera je schopna vynechavat nektere parametry. Hodnota alpha/lambda vychazi optimalne jako pomerne nizka, tedy nedochazi k tak velke penalizaci. MAPE vychazi ~11%, coz je podle me velmi dobre

In [38]:
```
el = ElasticNet(alpha=0.1, l1_ratio=0.95)

el.fit(X_train, y_train)

mape(y_test, el.predict(X_test))
```

Out[38]:
```
0.1133152803325097
```

Rozhodovaci stromy

Zakladni regresni strom

Pouzit Randomized Search (podobny jako grid, ale netestuje vsechny kombinace, jen nahodny vyber)

In [39]:
```
from sklearn.tree import DecisionTreeRegressor
```

In [40]:
```
dtr = DecisionTreeRegressor()
```

In [41]:
```
random_grid = {
    "ccp_alpha": np.linspace(0.0001, 0.1, 10), # 10 ruznych ccp
    "criterion": ["squared_error", "friedman_mse", "absolute_error", "poisso
    "min_samples_leaf": [1, 2, 5, 10]
}
```

In [42]:
```
from sklearn.model_selection import RandomizedSearchCV
```

In [43]:
```
randomizerCV = RandomizedSearchCV(estimator = dtr,
                                  param_distributions = random_grid,
                                  n_iter = 3,
                                  cv=2, verbose=2,
                                  random_state = 1)
```

In [44]:
```
randomizerCV.fit(X_train, y_train)
```

```
Fitting 2 folds for each of 3 candidates, totalling 6 fits
[CV] END ccp_alpha=0.0112, criterion=poisson, min_samples_leaf=2; total tim
e=   1.4s
[CV] END ccp_alpha=0.0112, criterion=poisson, min_samples_leaf=2; total tim
e=   1.4s
[CV] END ccp_alpha=0.0223, criterion=absolute_error, min_samples_leaf=5; to
tal time= 6.7min
[CV] END ccp_alpha=0.0223, criterion=absolute_error, min_samples_leaf=5; to
tal time= 6.5min
[CV] END ccp_alpha=0.0001, criterion=poisson, min_samples_leaf=5; total tim
e=   0.8s
[CV] END ccp_alpha=0.0001, criterion=poisson, min_samples_leaf=5; total tim
e=   0.8s
```

Out[44]:

```
▸ RandomizedSearchCV
▸ estimator: DecisionTreeRegressor
    ▸ DecisionTreeRegressor
```

In [45]:

```python
# nalezeni optimalnich parametru pro nas strom
randomizerCV.best_params_
```

Out[45]:

```
{'min_samples_leaf': 5, 'criterion': 'poisson', 'ccp_alpha': 0.0001}
```

In [46]:

```python
regression_tree = DecisionTreeRegressor(min_samples_leaf = 5,
                                        criterion = 'poisson',
                                        ccp_alpha = 0.1)
```

In [47]:

```python
regression_tree.fit(X_train, y_train)
```

Out[47]:

```
▾ DecisionTreeRegressor
DecisionTreeRegressor(ccp_alpha=0.1, criterion='poisson', min_sampl
es_leaf=5)
```

In [48]:

```python
# velmi nizka out-of-sample chyba
mape(y_test, regression_tree.predict(X_test))
```

Out[48]:

```
0.0429253696015026
```

Bagging

100 bootstrapovanych (nahodny vyber pozorovani s vracenim) regresnich stromu. Vysledna chyba vznikne zprumerovanim.

In [49]:

```python
from sklearn.ensemble import BaggingRegressor
```

In [50]:

```python
bagging = BaggingRegressor(n_estimators=100, random_state=1)
```

In [51]:

```python
bagging.fit(X_train, y_train)
```

Out[51]:
```
▾ BaggingRegressor
BaggingRegressor(n_estimators=100, random_state=1)
```

In [52]:
```
mape(y_test, bagging.predict(X_test))
```

Out[52]:
```
0.02806644129803859
```

Velmi dobry vysledek, zatim nejlepsi. Mozna byl nas puvodni strom trochu pre-uceny, coz se nam podarilo baggingem vyresit.

Random forest

Opet 100 nahodnych stromu, vcetne nahodneho vyberu promennych. Pouzity stejne parametry jako pri klasickem stromu.

In [53]:
```
from sklearn.ensemble import RandomForestRegressor
```

In [54]:
```
random_forest = RandomForestRegressor(n_estimators = 100,
                                      min_samples_leaf = 5,
                                      criterion = 'poisson',
                                      ccp_alpha = 0.1,
                                      random_state=1)
```

In [55]:
```
random_forest.fit(X_train, y_train)
```

Out[55]:
```
▾ RandomForestRegressor
RandomForestRegressor(ccp_alpha=0.1, criterion='poisson', min_sampl
es_leaf=5,
                      random_state=1)
```

In [56]:
```
mape(y_test, random_forest.predict(X_test))
```

Out[56]:
```
0.04078963466466962
```

Random forest ma sice mensi chybu nez puvodni strom, ale neni tak dobry jako obycejny Bagging. Pravdepodobne by pomohlo testovat vice ruznych settingu random forestu a najit nejaky lepsi.

Boosting

Predikce chyby predchoziho stromu. Metoda: gradient.

In [57]:
```
from sklearn.ensemble import HistGradientBoostingRegressor
```

In [58]:
```
boosting = HistGradientBoostingRegressor(loss = 'poisson',
                                         max_iter = 100,
```

```
                                        min_samples_leaf = 5)
```

In [59]:
```
boosting.fit(X_train, y_train)
```

Out[59]:
```
▾                HistGradientBoostingRegressor
HistGradientBoostingRegressor(loss='poisson', min_samples_leaf=5)
```

In [60]:
```
mape(y_test, boosting.predict(X_test))
```

Out[60]:
```
0.06874158115299706
```

Zde si takto "vysokou" chybu nedokazu uplne vysvetlit. Mozna zkusit upravit learning rate (default je 0.1) nebo treba L2 regularizaci, kterou model nabizi.

Support Vector Regression

Spise pro zajimavost, nemam tolik zkusenosti s vyberem parametru pro kernely a trenink trval velmi, velmi dlouho.

Jinak pokud tomu dobre rozumim, tak SVR je vlastne celkem podobna klasicke regresi. Diky pouziti kernelu je ale mozne dobre fitovat model i na nelinearni data.

In [61]:
```
from sklearn.svm import SVR
```

In [62]:
```
kernels = ["linear", "poly", "rbf"]
```

In [63]:
```
for kernel in kernels:
    model = SVR(kernel = kernel)
    model.fit(X_train, y_train)
    yhat = model.predict(X_test)
    print(f"{kernel}: {mape(y_test, yhat): .4f}")
```

```
linear:  0.1671
poly:  0.2308
rbf:  0.2304
```

Jak jiz mozna bylo mozne videt drive, nase data jsou dobre rozdelitelna i linearne (dobre vysledky regularizovane linearni regrese). Tim si vysvetluji horsi skore SVR s pouzitim nelinearnich kernelu nez kernelu `linear`.

Neuronova sit

In [29]:
```
from keras.models import Sequential
from keras.layers import Dense, Dropout, BatchNormalization
```

Neuronka s jednou skrytou vrstvou

- Input layer = 326 neuronu
- Hidden layer = 16 neuronu
- Batch normalizace vstupu
- Dropout 20% proti over fittingu
- Output layer = 1 neuron

Vsechny aktivace RELU

Batch size 16

In [30]:
```
# Vytvoření a kompilace modelu
model = Sequential()
model.add(Dense(16, input_shape=(326,), activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.2))
model.add(Dense(1, activation='relu'))

model.compile(loss='mean_squared_error', optimizer='adam',
              metrics='mean_absolute_percentage_error')

model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_1 (Dense)             (None, 16)                5232

 batch_normalization (BatchN  (None, 16)               64
 ormalization)

 dropout (Dropout)           (None, 16)                0

 dense_2 (Dense)             (None, 1)                 17

=================================================================
Total params: 5,313
Trainable params: 5,281
Non-trainable params: 32
_________________________________________________________________
```

In [35]:
```
model.fit(X_train, y_train,
          epochs=20, batch_size=16,
          verbose=1)
```

```
Epoch 1/20
4675/4675 [==============================] - 14s 3ms/step - loss: 10318147
2.0000 - mean_absolute_percentage_error: 15.3554
Epoch 2/20
4675/4675 [==============================] - 9s 2ms/step - loss: 100858056.
0000 - mean_absolute_percentage_error: 15.0977
Epoch 3/20
4675/4675 [==============================] - 11s 2ms/step - loss: 99419680.
0000 - mean_absolute_percentage_error: 14.9246
Epoch 4/20
4675/4675 [==============================] - 11s 2ms/step - loss: 99728944.
0000 - mean_absolute_percentage_error: 14.9564
Epoch 5/20
4675/4675 [==============================] - 10s 2ms/step - loss: 98279192.
0000 - mean_absolute_percentage_error: 14.8108
Epoch 6/20
4675/4675 [==============================] - 10s 2ms/step - loss: 96285328.
0000 - mean_absolute_percentage_error: 14.7581
Epoch 7/20
4675/4675 [==============================] - 10s 2ms/step - loss: 96448688.
0000 - mean_absolute_percentage_error: 14.6732
Epoch 8/20
4675/4675 [==============================] - 10s 2ms/step - loss: 96060464.
0000 - mean_absolute_percentage_error: 14.7116
Epoch 9/20
4675/4675 [==============================] - 10s 2ms/step - loss: 94731232.
0000 - mean_absolute_percentage_error: 14.5567
Epoch 10/20
4675/4675 [==============================] - 11s 2ms/step - loss: 95507864.
0000 - mean_absolute_percentage_error: 14.6669
Epoch 11/20
4675/4675 [==============================] - 11s 2ms/step - loss: 94675704.
0000 - mean_absolute_percentage_error: 14.6384
Epoch 12/20
4675/4675 [==============================] - 9s 2ms/step - loss: 94830560.0
000 - mean_absolute_percentage_error: 14.6619
Epoch 13/20
4675/4675 [==============================] - 11s 2ms/step - loss: 94147432.
0000 - mean_absolute_percentage_error: 14.6477
Epoch 14/20
4675/4675 [==============================] - 11s 2ms/step - loss: 94580928.
0000 - mean_absolute_percentage_error: 14.7146
Epoch 15/20
4675/4675 [==============================] - 11s 2ms/step - loss: 94750824.
0000 - mean_absolute_percentage_error: 14.6743
Epoch 16/20
4675/4675 [==============================] - 10s 2ms/step - loss: 92805576.
0000 - mean_absolute_percentage_error: 14.5660
Epoch 17/20
4675/4675 [==============================] - 11s 2ms/step - loss: 93521728.
0000 - mean_absolute_percentage_error: 14.5580
Epoch 18/20
4675/4675 [==============================] - 11s 2ms/step - loss: 93022568.
0000 - mean_absolute_percentage_error: 14.6101
Epoch 19/20
4675/4675 [==============================] - 11s 2ms/step - loss: 93330144.
```

```
0000 - mean_absolute_percentage_error: 14.5814
Epoch 20/20
4675/4675 [==============================] - 11s 2ms/step - loss: 93659648.
0000 - mean_absolute_percentage_error: 14.6387
```

Out[35]: <keras.callbacks.History at 0x7f7539652da0>

In [47]:
```
# in-sample. Je mozne, ze keras nasobi MAPE *2?
mape(y_train, model.predict(X_train))
```

```
2338/2338 [==============================] - 5s 2ms/step
```

Out[47]: 0.07272346333201705

In [36]:
```
# out-of-sample
mape(y_test, model.predict(X_test))
```

```
585/585 [==============================] - 2s 4ms/step
```

Out[36]: 0.07269192021798271

Jelikoz se data zdaji byt pomerne linearni, prvni neuronku jsem zkusil spise jednodussi, s pouze jednou skrytou vrstvou. Out-of-sample MAPE ~7 procent.

Neuronka s dvema skrytymi vrstvami

- Input layer = 326 neuronu
- Hidden layer = 16 neuronu
- Batch normalizace vstupu
- Dropout 20%
- Hidden layer = 24 neuronu
- Dropout 10%
- Output layer = 1 neuron

Vsechny aktivace RELU

Batch size 12

In [49]:
```
# Vytvoření a kompilace modelu
model2 = Sequential()
model2.add(Dense(16, input_shape=(326,), activation='relu'))
model2.add(BatchNormalization())
model2.add(Dropout(0.2))
model2.add(Dense(24, activation='relu'))
model2.add(Dropout(0.1))
model2.add(Dense(1, activation='relu'))

model2.compile(loss='mean_squared_error', optimizer='adam',
               metrics='mean_absolute_percentage_error')

model2.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense_9 (Dense)             (None, 16)                5232      
                                                                 
 batch_normalization_3 (Batc  (None, 16)               64        
 hNormalization)                                                 
                                                                 
 dropout_5 (Dropout)         (None, 16)                0         
                                                                 
 dense_10 (Dense)            (None, 24)                408       
                                                                 
 dropout_6 (Dropout)         (None, 24)                0         
                                                                 
 dense_11 (Dense)            (None, 1)                 25        
                                                                 
=================================================================
Total params: 5,729
Trainable params: 5,697
Non-trainable params: 32
_________________________________________________________________
```

In [53]:

```
model2.fit(X_train, y_train,
          epochs=20, batch_size=12,
          verbose=1)
```

```
Epoch 1/20
6233/6233 [==============================] - 15s 2ms/step - loss: 11434965
6.0000 - mean_absolute_percentage_error: 16.2468
Epoch 2/20
6233/6233 [==============================] - 15s 2ms/step - loss: 11358037
6.0000 - mean_absolute_percentage_error: 16.2197
Epoch 3/20
6233/6233 [==============================] - 14s 2ms/step - loss: 11299057
6.0000 - mean_absolute_percentage_error: 16.1990
Epoch 4/20
6233/6233 [==============================] - 14s 2ms/step - loss: 11185695
2.0000 - mean_absolute_percentage_error: 16.1351
Epoch 5/20
6233/6233 [==============================] - 14s 2ms/step - loss: 11302000
8.0000 - mean_absolute_percentage_error: 16.1746
Epoch 6/20
6233/6233 [==============================] - 14s 2ms/step - loss: 11216140
8.0000 - mean_absolute_percentage_error: 16.1497
Epoch 7/20
6233/6233 [==============================] - 15s 2ms/step - loss: 11182761
6.0000 - mean_absolute_percentage_error: 16.1415
Epoch 8/20
6233/6233 [==============================] - 15s 2ms/step - loss: 11182588
8.0000 - mean_absolute_percentage_error: 16.0981
Epoch 9/20
6233/6233 [==============================] - 15s 2ms/step - loss: 11038562
4.0000 - mean_absolute_percentage_error: 16.0056
Epoch 10/20
6233/6233 [==============================] - 15s 2ms/step - loss: 11109351
2.0000 - mean_absolute_percentage_error: 16.0295
Epoch 11/20
6233/6233 [==============================] - 14s 2ms/step - loss: 11070683
2.0000 - mean_absolute_percentage_error: 16.0019
Epoch 12/20
6233/6233 [==============================] - 14s 2ms/step - loss: 11070185
6.0000 - mean_absolute_percentage_error: 15.9697
Epoch 13/20
6233/6233 [==============================] - 15s 2ms/step - loss: 11051803
2.0000 - mean_absolute_percentage_error: 15.9662
Epoch 14/20
6233/6233 [==============================] - 15s 2ms/step - loss: 11008112
8.0000 - mean_absolute_percentage_error: 15.9082
Epoch 15/20
6233/6233 [==============================] - 14s 2ms/step - loss: 10973395
2.0000 - mean_absolute_percentage_error: 15.8726
Epoch 16/20
6233/6233 [==============================] - 14s 2ms/step - loss: 10925093
6.0000 - mean_absolute_percentage_error: 15.9058
Epoch 17/20
6233/6233 [==============================] - 14s 2ms/step - loss: 10939073
6.0000 - mean_absolute_percentage_error: 15.8735
Epoch 18/20
6233/6233 [==============================] - 15s 2ms/step - loss: 10936861
6.0000 - mean_absolute_percentage_error: 15.8905
Epoch 19/20
6233/6233 [==============================] - 14s 2ms/step - loss: 10802593
```

```
6.0000 - mean_absolute_percentage_error: 15.8455
Epoch 20/20
6233/6233 [==============================] - 15s 2ms/step - loss: 10831861
6.0000 - mean_absolute_percentage_error: 15.8034
```

Out[53]:
```
<keras.callbacks.History at 0x7f75390238e0>
```

In [54]:
```
mape(y_test, model2.predict(X_test))
```

```
585/585 [==============================] - 1s 2ms/step
```

Out[54]:
```
0.0732175049171604
```

Zkusil jsem trochu slozitejsi neuronku s pridanou druhou skrytou vrstvou. Prislo mi, ze se ztratova funkce snizovala pomalu, zkusil jsem tedy snizit velikost davky, coz prilis nepomohlo. Vysledky nejsou o moc lepsi ani horsi nez jednodussi neuronova sit.

Zaver

Myslim, ze se ukazalo, ze ceny letenek jsou dobre predikovatelne a to i pomoci jednodussich modelu. Oproti puvodni benchmark linearni regresi performovali vsechny dalsi modely vyborne. Krome `class` jsem pouzil vsechny sloupce, vcetne kategorialnich pomoci one hot encodingu.

Jako metriku chyby jsem zvolil MAPE (Mean Absolute Percentage Error), tedy prumernou absolutni procentualni chybu. Vysledna chyba se da interpretovat jako prumerna procentualni odchylka predikce od skutecnych hodnot.

Vyber nejlepsiho modelu

Jelikoz dobrych predikcnich schopnosti dosahovaly i jednodussi modely, myslim, ze je vhodne vybrat je. A to primarne z duvodu jejich snadne uchopitelnosti i rychlosti treninku.

Naprosto nejlepsich vysledku dosahly regresni stromy za pouziti bagging metody (bootstrap + aggregate). MAPE tohoto modelu byla pouze ~2.8%, coz je fantasticka hodnota.

I standardni regresni strom, nebo model random forest dosahl dobrych vysledku a MAPE ~4.2% a ~4%. U jednoho stromu mam podezreni na over-fitting, u random forestu si myslim, ze jsem nenalezl optimalni parametry.

Dalsim vhodnym modelem by mohla byt linearni regrese regularizovana pomoci elastic net. Pri pouziti L1 (Lasso) regularizace dosahl tento model out-of-sample chyby asi 11%, coz na linearni regresi neni vubec spatne. Hledani optimalnich parametru vsak trvalo pomerne dlouho.

Myslim, ze v pripade aktualnich dat nema vyznam vuzivat neuronove site. Ackoliv i jednoducha sit mela vcelku dobre predikcni schopnosti, neni lepsi nez rozhodovaci stromy a jeji trenink a interpretace je slozitejsi. Je mozne, ze pri nalezeni lepsich hyper-parametru, by mohla neuronka dosahnout stejne kvality predikci jako stromy. Aktivacni funkce vsech neuronu jsem vybral RELU.

K Support Vector modelum se radsi moc nevyjadruji :D Myslim, ze by melo byt mozne je zlepsit. Jejich trenovani trvalo ale vyrazne nejdele ze vsech modelu v tomhle notebooku, takze jsem se jim moc nevenoval.

Jakou miru chyby je mozne ocekavat?

Rekl bych, ze ocekavatelna mira chyby je rovna hodnotam zminenym vyse. Vsechny uvedene MAPE odchylky jsou pocitany out-of-sample, tedy na validacnich 20% puvodnich dat, ktere nebyly pouzity pro trenink. Diky vetsimu rozsahu dat bylo dost pozorovani pro trenink i pro testovani, a nezaznamenal jsem vyrazny over fitting.