

VES_prognose

September 22, 2024

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[1]: import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from datetime import datetime, date, time
import matplotlib.pyplot as plt
from pandas.plotting import scatter_matrix
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import GridSearchCV

[2]: # ielādē dotos datus
path = "C:/Users/ilzep/Documents/SadalesTikls/"
grob = "GrobinasVES.xlsx"
energ = pd.read_excel(path+grob)

energ['datums'] = pd.to_datetime(energ['datums'], format='%d.%m.%Y')
energ['laiks'] = pd.to_datetime(energ['laiks'], format='%H:%M:%S')
energ['laiks'] = energ['laiks'].dt.time
energ['datums'] = energ['datums'].dt.date

energ['DateTime'] = energ.apply(lambda row: datetime.combine(row['datums'],
↪row['laiks']), axis=1)
energ.drop(['datums', 'laiks'], axis=1, inplace=True)

[3]: # ielādē un apvieno meteoroloģisko datu failus
files = [
    "veja_atrums.xlsx", #fakt
    "veja_atr_minim.xlsx",
    "brazmas_stunda.xlsx",
    "veja_virziens.xlsx", # fakt
    "temperatura.xlsx", #fakt
    "mitrums.xlsx", #fakt
    "spiediens.xlsx" # fakt
]
meteo = None
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for file in files:
    df = pd.read_excel(path+file)
    df = df.drop([0]).reset_index(drop=True)
    df.columns = df.iloc[0]
    df = df.drop(0).reset_index(drop=True)

    df_melted = df.melt(id_vars=['Datums'], var_name='laiks',
↳value_name='Value')
    df_melted['Value'] = pd.to_numeric(df_melted['Value'])
    column_name = file.split('.')[0]
    df_melted = df_melted[['Datums', 'laiks', 'Value']].rename(columns={'Value':
↳column_name})
    df_melted['Datums'] = pd.to_datetime(df_melted['Datums'], format='%d.%m.%Y')
    df_melted['laiks'] = pd.to_datetime(df_melted['laiks'], format='%H:%M')
    df_melted['laiks'] = df_melted['laiks'].dt.time
    df_melted['DateTime'] = df_melted.apply(lambda row: datetime.
↳combine(row['Datums'], row['laiks']), axis=1)
    df_melted.drop(['Datums', 'laiks'], axis=1, inplace=True)
    if meteo is None:
        meteo = df_melted
    else:
        meteo = pd.merge(meteo, df_melted, on=['DateTime'], how='outer')

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[4]: # gaisa blīvuma aprēķins
e0 = 610.5
T1 = 17.269
T2 = 237.3
R = 287

meteo['E'] = e0 * np.exp((T1 * meteo['temperatura']) / (T2 +
↳meteo['temperatura']))
meteo['e'] = meteo['E'] * meteo['mitrums'] / 100
meteo['blivums'] = (meteo['spiediens']*100 / (R * (meteo['temperatura']+273)))
↳* (1 - (0.378 * meteo['e'] / (meteo['spiediens']*100)))
meteo = meteo.drop(columns=['E', 'e'])

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[5]: meteo['atrums^3'] = meteo['veja_atrums']**3
meteo['brazmas_stunda^3'] = meteo['brazmas_stunda']**3
meteo['vejs_vid'] = (meteo['veja_atr_minim'] + meteo['brazmas_stunda'])/2
meteo['vejs_vid^3'] = meteo['vejs_vid']**3
meteo['brazmainums'] = meteo['brazmas_stunda'] - meteo['veja_atr_minim']

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[6]: # sadalu meteo datus tajos, kam ir zināms ģenerētās enerģijas daudzums, un
↳tajos, kam jāprognozē
split_date = pd.to_datetime('01.06.2023', format='%d.%m.%Y')
meteo_maijs = meteo[meteo['DateTime'] < split_date]

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meteo_jun_jul = meteo[meteo['DateTime'] >= split_date]
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[7]: dati = pd.merge(energ, meteo_maijs, on=['DateTime'], how='inner')
dati_cleaned = dati.dropna()
```

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[8]: # aprēķinu korelāciju starp visiem lielumiem
kolonnas = ['kWh', 'veja_atrums', 'atrums^3', 'vejs_vid', 'vejs_vid^3',
            'brazmas_stunda', 'brazmas_stunda^3', 'brazmainums', 'veja_atr_minim',
            'blivums', 'mitrums', 'temperatura']
mat = dati[kolonnas]
correlation_matrix = mat.corr()
correlation_matrix
```

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[8]:
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	kWh	veja_atrums	atrums^3	vejs_vid	vejs_vid^3 \
kWh	1.000000	0.659993	0.744639	0.651503	0.726409
veja_atrums	0.659993	1.000000	0.894150	0.925511	0.841920
atrums^3	0.744639	0.894150	1.000000	0.821065	0.904733
vejs_vid	0.651503	0.925511	0.821065	1.000000	0.901390
vejs_vid^3	0.726409	0.841920	0.904733	0.901390	1.000000
brazmas_stunda	0.643419	0.919003	0.811247	0.996917	0.894401
brazmas_stunda^3	0.730472	0.837518	0.892318	0.902009	0.992004
brazmainums	0.629879	0.905231	0.794590	0.986369	0.880274
veja_atr_minim	0.442764	0.577437	0.554160	0.583023	0.569123
blivums	0.072187	-0.199605	-0.129487	-0.199980	-0.137890
mitrums	0.003715	-0.295422	-0.109106	-0.302335	-0.137246
temperatura	-0.160282	0.157436	0.053207	0.162812	0.066556

	brazmas_stunda	brazmas_stunda^3	brazmainums \
kWh	0.643419	0.730472	0.629879
veja_atrums	0.919003	0.837518	0.905231
atrums^3	0.811247	0.892318	0.794590
vejs_vid	0.996917	0.902009	0.986369
vejs_vid^3	0.894401	0.992004	0.880274
brazmas_stunda	1.000000	0.902434	0.996239
brazmas_stunda^3	0.902434	1.000000	0.896436
brazmainums	0.996239	0.896436	1.000000
veja_atr_minim	0.517482	0.492699	0.441388
blivums	-0.221352	-0.153117	-0.243370
mitrums	-0.307955	-0.141038	-0.311956
temperatura	0.185395	0.086488	0.209009

	veja_atr_minim	blivums	mitrums	temperatura
kWh	0.442764	0.072187	0.003715	-0.160282
veja_atrums	0.577437	-0.199605	-0.295422	0.157436
atrums^3	0.554160	-0.129487	-0.109106	0.053207
vejs_vid	0.583023	-0.199980	-0.302335	0.162812
vejs_vid^3	0.569123	-0.137890	-0.137246	0.066556

brazmas_stunda	0.517482	-0.221352	-0.307955	0.185395
brazmas_stunda^3	0.492699	-0.153117	-0.141038	0.086488
brazmainums	0.441388	-0.243370	-0.311956	0.209009
veja_atr_minim	1.000000	0.111100	-0.108419	-0.144132
blivums	0.111100	1.000000	0.501110	-0.964320
mitrums	-0.108419	0.501110	1.000000	-0.643505
temperatura	-0.144132	-0.964320	-0.643505	1.000000

```
[9]: # Linear Regression
kol_LR = ['atrums^3', 'blivums', 'brazmainums', 'temperatura']
X = dati_cleaned[kol_LR]
y = dati_cleaned['kWh']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    ↪random_state=42)
model_LR = LinearRegression()
model_LR.fit(X_train, y_train)

y_LR = model_LR.predict(X_test)
rmse_LR = np.sqrt(mean_squared_error(y_test, y_LR))
r2_LR = r2_score(y_test, y_LR)
```

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[10]: kolonnas = ['veja_atrums', 'atrums^3', 'vejs_vid', 'vejs_vid^3',
    ↪'brazmas_stunda', 'brazmas_stunda^3', 'brazmainums', 'veja_atr_minim',
    ↪'blivums', 'mitrums', 'temperatura']
X = dati_cleaned[kolonnas]
y = dati_cleaned['kWh']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    ↪random_state=42)
```

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[11]: # Gradient Boosting
gbr = GradientBoostingRegressor(random_state=42)
param_grid = {
    'n_estimators': [100, 200],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [2, 3, 4, 5],
    'min_samples_split': [2, 5, 10, 12],
    'min_samples_leaf': [1, 2, 4, 5],
    'subsample': [0.7, 0.8, 1.0]
}
grid_search = GridSearchCV(estimator=gbr, param_grid=param_grid, cv=5,
    ↪scoring='neg_mean_squared_error', n_jobs=-1, verbose=0)
grid_search.fit(X_train, y_train)

best_gbr = grid_search.best_estimator_
y_GBR = best_gbr.predict(X_test)
rmse_GBR = np.sqrt(mean_squared_error(y_test, y_GBR))
r2_GBR = r2_score(y_test, y_GBR)
```

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[12]: # Random Forest
rf = RandomForestRegressor(max_features='sqrt', random_state=42)
param_grid = {
    'n_estimators': [80, 100, 200, 300],
    'max_depth': [5, 7, 10, 20],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5,
    ↳scoring='neg_mean_squared_error', n_jobs=-1, verbose=0)
    ↳#neg_mean_squared_error

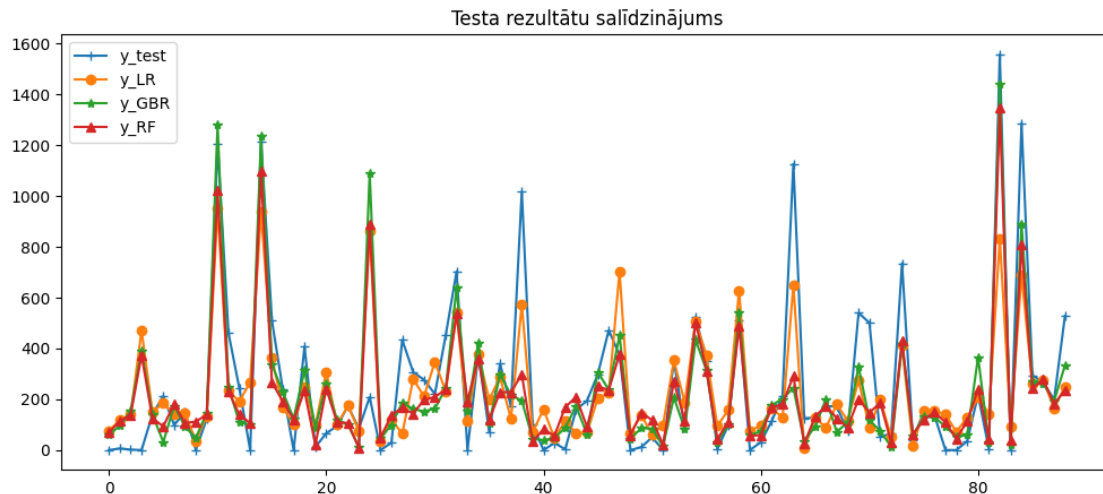
grid_search.fit(X_train, y_train)

best_rf = grid_search.best_estimator_
y_RF = best_rf.predict(X_test)
rmse_RF = np.sqrt(mean_squared_error(y_test, y_RF))
r2_RF = r2_score(y_test, y_RF)
```

```
[13]: # visu 3 metožu apvienojums
sal = pd.DataFrame(y_test)
sal['LR'] = y_LR
sal['GBR'] = y_GBR
sal['RF'] = y_RF
sal['total'] = (sal['LR']+sal['GBR']+sal['RF'])/3
rmse_tot = np.sqrt(mean_squared_error(y_test, sal['total']))
r2_tot = r2_score(y_test, sal['total'])
```

```
[14]: # 3 metožu testa rezultātu salīdzinājums
x = np.arange(89)
plt.figure(figsize=(12, 5))
plt.plot(x, y_test, label='y_test', marker='+')
plt.plot(x, y_LR, label='y_LR', marker='o')
plt.plot(x, y_GBR, label='y_GBR', marker='*')
plt.plot(x, y_RF, label='y_RF', marker='^')

plt.legend()
plt.title('Testa rezultātu salīdzinājums')
plt.show()
```



```
[15]: # 3 metožu skaitliskais novērtējums
modeli = {
    'Model': ['Linear Regression', 'Gradient Boosting', 'Random Forest', 'Total'],
    'RMSE': [rmse_LR, rmse_GBR, rmse_RF, rmse_tot],
    'R²': [r2_LR, r2_GBR, r2_RF, r2_tot]
}
vertejums = pd.DataFrame(modeli)
vertejums
```

```
[15]:
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	Model	RMSE	R ²
0	Linear Regression	199.111650	0.614909
1	Gradient Boosting	199.618315	0.612946
2	Random Forest	193.004482	0.638170
3	Total	188.646323	0.654326

```
[16]: # dati prognozēšanai
meteo_jun_jul = meteo_jun_jul.dropna()
new_data = meteo_jun_jul[kolonnas]
dati_LR = meteo_jun_jul[kol_LR]
```

```
[17]: # prognozēšana
predictions_GBR = best_gbr.predict(new_data)
predictions_RF = best_rf.predict(new_data)
predictions_LR = model_LR.predict(dati_LR)
```

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[18]: results = meteo_jun_jul[['DateTime']].copy()
results['LR'] = predictions_LR
results['GBR'] = predictions_GBR
results['RF'] = predictions_RF
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results['kWh'] = (results['LR']+results['GBR']+results['RF'])/3  
results = results.drop(columns=['LR', 'GBR', 'RF'])
```

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[19]: results.to_excel(path+'VES_prognose.xlsx', index=False)
```