NYC Yellow Taxi Data

- Demand prediction in Jaunary, 2015
- Using public data from BigQuery

1. Preprocessing

In [3]:
```
import pandas as pd
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.linear_model import LinearRegression
import seaborn as sns
import numpy as np
import warnings
import matplotlib.pyplot as plt
from ipywidgets import interact
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error

import os
from numpy.random import permutation
from sklearn import svm, datasets

from sacred import Experiment
from sacred.observers import FileStorageObserver

from xgboost import XGBRegressor
from lightgbm import LGBMRegressor
from sklearn.ensemble import RandomForestRegressor

import json

plt.style.use('ggplot')
warnings.filterwarnings('ignore')
%config InlineBackend.figure_format = 'retina'

PROJECT_ID='mobility-320516'
```

In [4]:
```
%%time
base_query = """
WITH base_data AS
(
  SELECT nyc_taxi.*, gis.* EXCEPT (zip_code_geom)
  FROM (
    SELECT *
    FROM `bigquery-public-data.new_york_taxi_trips.tlc_yellow_trips_2015
`
    WHERE
        EXTRACT(MONTH from pickup_datetime) = 1
        and pickup_latitude  <= 90 and pickup_latitude >= -90
    ) AS nyc_taxi
  JOIN (
    SELECT zip_code, state_code, state_name, city, county, zip_code_geom
    FROM `bigquery-public-data.geo_us_boundaries.zip_codes`
    WHERE state_code='NY'
    ) AS gis
  ON ST_CONTAINS(zip_code_geom, st_geogpoint(pickup_longitude, pickup_la
titude))
)

SELECT
    zip_code,
    DATETIME_TRUNC(pickup_datetime, hour) as pickup_hour,
    EXTRACT(MONTH FROM pickup_datetime) AS month,
    EXTRACT(DAY FROM pickup_datetime) AS day,
    CAST(format_datetime('%u', pickup_datetime) AS INT64) -1 AS weekday,
    EXTRACT(HOUR FROM pickup_datetime) AS hour,
    CASE WHEN CAST(FORMAT_DATETIME('%u', pickup_datetime) AS INT64) IN
 (6, 7) THEN 1 ELSE 0 END AS is_weekend,
    COUNT(*) AS cnt
FROM base_data
GROUP BY zip_code, pickup_hour, month, day, weekday, hour, is_weekend
ORDER BY pickup_hour


"""

base_df = pd.read_gbq(query=base_query, dialect='standard', project_id=P
ROJECT_ID)
```

```
Downloading: 100%|██████████| 87020/87020 [00:06<00:00, 13016.79rows/s]

CPU times: user 2.53 s, sys: 241 ms, total: 2.77 s
Wall time: 27 s
```

- Extract data with one-hour unit from BigQuery
- Change geographic coordinate to zipcode with reverse geocoding

In [5]:
```
base_df.head()
```

Out[5]:

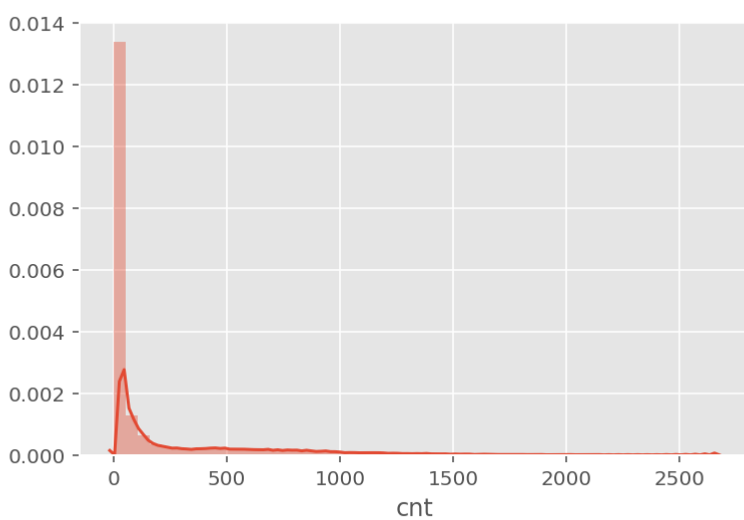
	zip_code	pickup_hour	month	day	weekday	hour	is_weekend	cnt
0	10039	2015-01-01	1	1	3	0	0	9
1	11221	2015-01-01	1	1	3	0	0	34
2	10037	2015-01-01	1	1	3	0	0	26
3	10004	2015-01-01	1	1	3	0	0	139
4	11238	2015-01-01	1	1	3	0	0	95

In [6]:
```
def split_train_and_test(df, date):
    train_df = df[df['pickup_hour'] < date]
    test_df = df[df['pickup_hour'] >= date]
    return train_df, test_df
```

Data distribution

In [7]:
```
sns.distplot(base_df['cnt'])
```

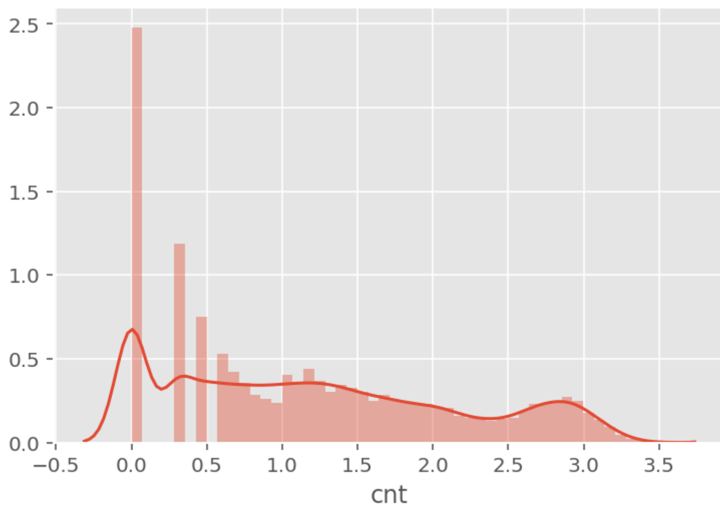
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff878f12640>



- The distribution is skewed right

In [8]:
```
sns.distplot(np.log10(base_df['cnt']))
```

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff8975dfe50>



- Performed log on count

In [9]:
```
base_df['log_cnt'] = np.log10(base_df['cnt'])
```

In [10]:
```
base_df.head()
```

Out[10]:

	zip_code	pickup_hour	month	day	weekday	hour	is_weekend	cnt	log_cnt
0	10039	2015-01-01	1	1	3	0	0	9	0.954243
1	11221	2015-01-01	1	1	3	0	0	34	1.531479
2	10037	2015-01-01	1	1	3	0	0	26	1.414973
3	10004	2015-01-01	1	1	3	0	0	139	2.143015
4	11238	2015-01-01	1	1	3	0	0	95	1.977724

Train/Test set split

In [11]:
```
train_df, test_df = split_train_and_test(base_df, '2015-01-24')
```

In [12]:
```
train_df.head()
```

Out[12]:

	zip_code	pickup_hour	month	day	weekday	hour	is_weekend	cnt	log_cnt
0	10039	2015-01-01	1	1	3	0	0	9	0.954243
1	11221	2015-01-01	1	1	3	0	0	34	1.531479
2	10037	2015-01-01	1	1	3	0	0	26	1.414973
3	10004	2015-01-01	1	1	3	0	0	139	2.143015
4	11238	2015-01-01	1	1	3	0	0	95	1.977724

In [13]:
```
test_df.head()
```

Out[13]:

	zip_code	pickup_hour	month	day	weekday	hour	is_weekend	cnt	log_cnt
65118	10280	2015-01-24	1	24	5	0	1	26	1.414973
65119	10038	2015-01-24	1	24	5	0	1	145	2.161368
65120	10004	2015-01-24	1	24	5	0	1	88	1.944483
65121	10025	2015-01-24	1	24	5	0	1	332	2.521138
65122	11217	2015-01-24	1	24	5	0	1	91	1.959041

In [14]:
```
# removing unnecessary columns
del train_df['pickup_hour']
del test_df['pickup_hour']
```

In [15]:
```
y_train_raw = train_df.pop('cnt')
y_train_log = train_df.pop('log_cnt')
y_test_raw = test_df.pop('cnt')
y_test_log = test_df.pop('log_cnt')
```

In [16]:
```
x_train = train_df.copy()
x_test = test_df.copy()
```

In [17]:
```
x_train.head()
```

Out[17]:

	zip_code	month	day	weekday	hour	is_weekend
0	10039	1	1	3	0	0
1	11221	1	1	3	0	0
2	10037	1	1	3	0	0
3	10004	1	1	3	0	0
4	11238	1	1	3	0	0

2. Simple regression

- Baseline model for comparison

In [18]:
```
lr_reg = LinearRegression()
lr_reg.fit(x_train, y_train_log)
pred = lr_reg.predict(x_test)
pred
```

Out[18]:
```
array([1.32176716, 1.53056483, 1.55990004, ..., 0.84768815, 1.85457609,
       0.83129495])
```

In [19]:
```
def evaluation(y_true, y_pred):
    y_true, y_pred = np.array(y_true), np.array(y_pred)
    mape = np.mean(np.abs((y_true - y_pred) / y_true)) * 100
    mae = mean_absolute_error(y_true, y_pred)
    mse = mean_squared_error(y_true, y_pred)
    score = pd.DataFrame([mape, mae, mse], index=['mape', 'mae', 'mse'],
columns=['score']).T
    return score
```

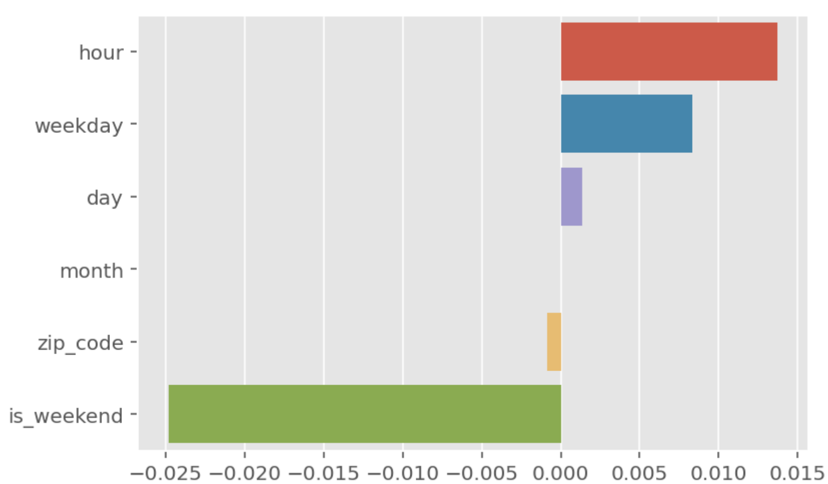
In [20]:
```
evaluation(y_test_raw, 10**pred)
```

Out[20]:

	mape	mae	mse
score	428.415375	126.535552	95916.687733

Coef significance

In [21]:
```
coef = pd.Series(lr_reg.coef_ , index=x_train.columns)
coef_sort = coef.sort_values(ascending=False)[:10]
sns.barplot(x=coef_sort.values , y=coef_sort.index);
```



save Logger

In [22]:
```
sl_ex = Experiment('nyc-demand-prediction_sl', interactive=True)

experiment_dir = os.path.join('./', 'experiments')
if not os.path.isdir(experiment_dir):
    os.makedirs(experiment_dir)
sl_ex.observers.append(FileStorageObserver.create(experiment_dir))
```

In [23]:
```
@sl_ex.config
def config():
    fit_intercept=True
    normalize=False
```

In [24]:
```
@sl_ex.capture
def get_model(fit_intercept, normalize):
    return LinearRegression(fit_intercept, normalize)
```

In [25]:
```
@sl_ex.main
def run(_log, _run):
    lr_reg = get_model()
    lr_reg.fit(x_train, y_train_raw)
    pred = lr_reg.predict(x_test)

    _log.info("Predict End")
    score = evaluation(y_test_raw, pred)
    _run.log_scalar('model_name', lr_reg.__class__.__name__)

    _run.log_scalar('metrics', score.to_dict())

    return score.to_dict()
```

In [26]:
```
experiment_result = sl_ex.run()
```

```
INFO - nyc-demand-prediction_sl - Running command 'run'
INFO - nyc-demand-prediction_sl - Started run with ID "6"
INFO - run - Predict End
INFO - nyc-demand-prediction_sl - Result: {'mape': {'score': 3190.20132
7875614}, 'mae': {'score': 185.28793226544403}, 'mse': {'score': 78953.
34266541619}}
INFO - nyc-demand-prediction_sl - Completed after 0:00:00
```

In [27]:
```
experiment_result.config
```

Out[27]:
```
{'fit_intercept': True, 'normalize': False, 'seed': 932323689}
```

In [28]:
```
def parsing_output(ex_id):
    with open(f'./experiments/{ex_id}/metrics.json') as json_file:
        json_data = json.load(json_file)
    with open(f'./experiments/{ex_id}/config.json') as config_file:
        config_data = json.load(config_file)

    output_df = pd.DataFrame(json_data['model_name']['values'], columns=
['model_name'], index=['score'])
    output_df['experiment_num'] = ex_id
    output_df['config'] = str(config_data)
    metric_df = pd.DataFrame(json_data['metrics']['values'][0])

    output_df = pd.concat([output_df, metric_df], axis=1)
    output_df = output_df.round(2)
    return output_df
```

In [29]:
```
parsing_output(1)
```

Out[29]:

	model_name	experiment_num	config	mae	mape	mse
score	LinearRegression	1	{'fit_intercept': True, 'normalize': False, 's...	185.29	3190.2	78953.34

3. Label Encoding

In [30]:
```
le = LabelEncoder()
base_df['zip_code_le'] = le.fit_transform(base_df['zip_code'])
```

In [31]:
```
base_df.head()
```

Out[31]:

	zip_code	pickup_hour	month	day	weekday	hour	is_weekend	cnt	log_cnt	zip_code_le
0	10039	2015-01-01	1	1	3	0	0	9	0.954243	36
1	11221	2015-01-01	1	1	3	0	0	34	1.531479	210
2	10037	2015-01-01	1	1	3	0	0	26	1.414973	34
3	10004	2015-01-01	1	1	3	0	0	139	2.143015	3
4	11238	2015-01-01	1	1	3	0	0	95	1.977724	226

In [32]:
```
train_df, test_df = split_train_and_test(base_df, '2015-01-24')
```

In [33]:
```
train_df.head()
```

Out[33]:

	zip_code	pickup_hour	month	day	weekday	hour	is_weekend	cnt	log_cnt	zip_code_le
0	10039	2015-01-01	1	1	3	0	0	9	0.954243	36
1	11221	2015-01-01	1	1	3	0	0	34	1.531479	210
2	10037	2015-01-01	1	1	3	0	0	26	1.414973	34
3	10004	2015-01-01	1	1	3	0	0	139	2.143015	3
4	11238	2015-01-01	1	1	3	0	0	95	1.977724	226

In [34]:
```
del train_df['zip_code']
del train_df['pickup_hour']
del test_df['zip_code']
del test_df['pickup_hour']
```

In [35]:
```
del train_df['log_cnt']
del test_df['log_cnt']
```

In [36]:
```
train_df.head()
```

Out[36]:

	month	day	weekday	hour	is_weekend	cnt	zip_code_le
0	1	1	3	0	0	9	36
1	1	1	3	0	0	34	210
2	1	1	3	0	0	26	34
3	1	1	3	0	0	139	3
4	1	1	3	0	0	95	226

In [37]:
```
y_train_raw = train_df.pop('cnt')
y_test_raw = test_df.pop('cnt')
```

In [38]:
```
x_train = train_df.copy()
x_test = test_df.copy()
```

4. XGBoost Regressor

In [39]:
```
xgb_ex = Experiment('nyc-demand-prediction_xgb', interactive=True)
xgb_ex.observers.append(FileStorageObserver.create(experiment_dir))
```

Save Logger

In [40]:
```
@xgb_ex.config
def config():
    max_depth=5
    learning_rate=0.1
    n_estimators=100
    n_jobs=-1
```

In [41]:
```
@xgb_ex.capture
def get_model(max_depth, learning_rate, n_estimators, n_jobs):
    return XGBRegressor(max_depth=max_depth, learning_rate=learning_rate
, n_estimators=n_estimators, n_jobs=n_jobs)
```

In [42]:
```
@xgb_ex.main
def run(_log, _run):
    global xgb_reg, xgb_pred
    xgb_reg = get_model()
    xgb_reg.fit(x_train, y_train_raw)
    xgb_pred = xgb_reg.predict(x_test)
    score = evaluation(y_test_raw, xgb_pred)

    _run.log_scalar('model_name', xgb_reg.__class__.__name__)
    _run.log_scalar('metrics', score.to_dict())

    return score.to_dict()
```

In [43]:
```
experiment_result = xgb_ex.run()
```

```
INFO - nyc-demand-prediction_xgb - Running command 'run'
INFO - nyc-demand-prediction_xgb - Started run with ID "7"
INFO - nyc-demand-prediction_xgb - Result: {'mape': {'score': 538.52015
61766146}, 'mae': {'score': 57.67873599873819}, 'mse': {'score': 16512.
3302373418}}
INFO - nyc-demand-prediction_xgb - Completed after 0:00:01
```

In [44]:
```
experiment_result.config
```

Out[44]:
```
{'max_depth': 5,
 'learning_rate': 0.1,
 'n_estimators': 100,
 'n_jobs': -1,
 'seed': 511081283}
```

In [45]:
```
parsing_output(2)
```

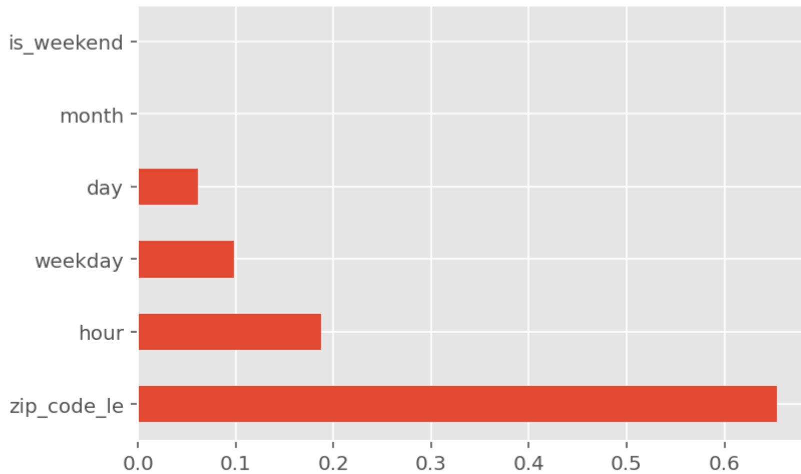
Out[45]:

	model_name	experiment_num	config	mae	mape	mse
score	XGBRegressor	2	{'learning_rate': 0.1, 'max_depth': 5, 'n_esti...	57.68	538.52	16512.33

Coef significance

In [46]:
```
feat_importances = pd.Series(xgb_reg.feature_importances_, index=x_train
.columns)
feat_importances.nlargest(15).plot(kind='barh')
```

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff879a2c820>



5. Lightgbm Regressor

In [47]:
```
lgbm_ex = Experiment('nyc-demand-prediction_lgbm', interactive=True)
lgbm_ex.observers.append(FileStorageObserver.create(experiment_dir))
```

Save Logger

In [48]:
```
@lgbm_ex.config
def config():
    num_leaves=31
    max_depth=-1
    learning_rate=0.1
    n_estimators=100
```

In [49]:
```
@lgbm_ex.capture
def get_model(num_leaves, max_depth, learning_rate, n_estimators):
    return LGBMRegressor(num_leaves=num_leaves, max_depth=max_depth, lea
rning_rate=learning_rate, n_estimators=n_estimators)
```

In [50]:
```python
@lgbm_ex.main
def run(_log, _run):
    global lgbm_reg, lgbm_pred
    lgbm_reg = get_model()
    lgbm_reg.fit(x_train, y_train_raw)
    lgbm_pred = lgbm_reg.predict(x_test)
    score = evaluation(y_test_raw, lgbm_pred)

    _run.log_scalar('model_name', lgbm_reg.__class__.__name__)
    _run.log_scalar('metrics', score.to_dict())

    return score.to_dict()
```

In [51]:
```python
experiment_result = lgbm_ex.run()
```

```
INFO - nyc-demand-prediction_lgbm - Running command 'run'
INFO - nyc-demand-prediction_lgbm - Started run with ID "8"
INFO - nyc-demand-prediction_lgbm - Result: {'mape': {'score': 421.6856
972338652}, 'mae': {'score': 48.24149103960721}, 'mse': {'score': 1375
5.684889975497}}
INFO - nyc-demand-prediction_lgbm - Completed after 0:00:00
```

In [52]:
```python
experiment_result.config
```

Out[52]:
```
{'num_leaves': 31,
 'max_depth': -1,
 'learning_rate': 0.1,
 'n_estimators': 100,
 'seed': 685162281}
```

In [53]:
```python
parsing_output(3)
```

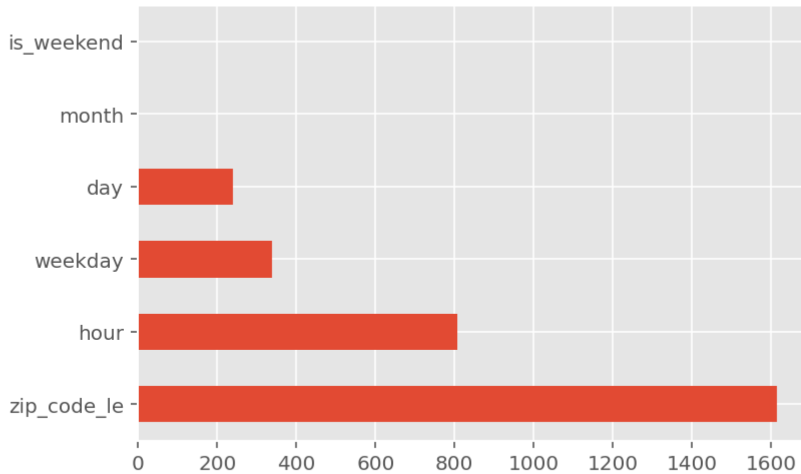
Out[53]:

	model_name	experiment_num	config	mae	mape	mse
score	LGBMRegressor	3	{'learning_rate': 0.1, 'max_depth': -1, 'n_est...	48.24	421.69	13755.68

Coef significance

In [54]:
```
feat_importances = pd.Series(lgbm_reg.feature_importances_, index=x_trai
n.columns)
feat_importances.nlargest(15).plot(kind='barh')
```

Out[54]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff879d675b0>



6. Random Forest Regressor

In [55]:
```
rf_ex = Experiment('nyc-demand-prediction_rf', interactive=True)
rf_ex.observers.append(FileStorageObserver.create(experiment_dir))
```

Save Logger

In [56]:
```
@rf_ex.config
def config():
    n_estimators=10
    n_jobs=-1
```

In [57]:
```
@rf_ex.capture
def get_model(n_estimators, n_jobs):
    return RandomForestRegressor(n_estimators=n_estimators, n_jobs=n_job
s)
```

In [58]:
```
@rf_ex.main
def run(_log, _run):
    global rf_reg, rf_pred
    rf_reg = get_model()
    rf_reg.fit(x_train, y_train_raw)
    rf_pred = rf_reg.predict(x_test)
    score = evaluation(y_test_raw, rf_pred)

    _run.log_scalar('model_name', rf_reg.__class__.__name__)
    _run.log_scalar('metrics', score.to_dict())

    return score.to_dict()
```

In [59]:
```
experiment_result = rf_ex.run()
```

```
INFO - nyc-demand-prediction_rf - Running command 'run'
INFO - nyc-demand-prediction_rf - Started run with ID "9"
INFO - nyc-demand-prediction_rf - Result: {'mape': {'score': 180.698414
51730736}, 'mae': {'score': 34.75248835722765}, 'mse': {'score': 11902.
818517943568}}
INFO - nyc-demand-prediction_rf - Completed after 0:00:00
```

In [60]:
```
experiment_result.config
```

Out[60]:
```
{'n_estimators': 10, 'n_jobs': -1, 'seed': 207159803}
```

In [61]:
```
parsing_output(4)
```

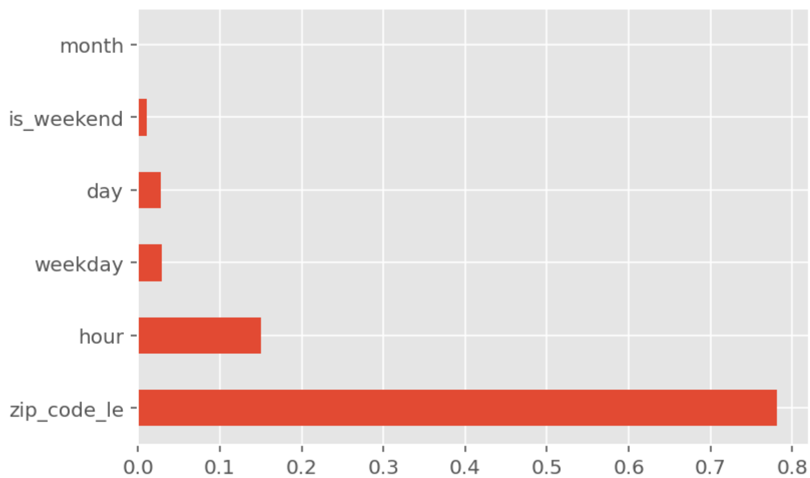
Out[61]:

	model_name	experiment_num	config	mae	mape	mse
score	RandomForestRegressor	4	{'n_estimators': 10, 'n_jobs': -1, 'seed': 682...	35.27	184.41	12195.66

Coef significance

In [62]:
```
feat_importances = pd.Series(rf_reg.feature_importances_, index=x_train.
columns)
feat_importances.nlargest(15).plot(kind='barh')
```

Out[62]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff8791bb160>



In [63]:
```
test_df.head()
```

Out[63]:

	month	day	weekday	hour	is_weekend	zip_code_le
65118	1	24	5	0	1	67
65119	1	24	5	0	1	35
65120	1	24	5	0	1	3
65121	1	24	5	0	1	22
65122	1	24	5	0	1	206

In [64]:
```
test_df['zip_code'] = le.inverse_transform(test_df['zip_code_le'])
```

The best model among all

In [68]:
```
pd.concat([parsing_output(1), parsing_output(2), parsing_output(3), pars
ing_output(4)])
```

Out[68]:

	model_name	experiment_num	config	mae	mape	mse
score	LinearRegression	1	{'fit_intercept': True, 'normalize': False, 's...	185.29	3190.20	78953.34
score	XGBRegressor	2	{'learning_rate': 0.1, 'max_depth': 5, 'n_esti...	57.68	538.52	16512.33
score	LGBMRegressor	3	{'learning_rate': 0.1, 'max_depth': -1, 'n_est...	48.24	421.69	13755.68
score	RandomForestRegressor	4	{'n_estimators': 10, 'n_jobs': -1, 'seed': 682...	35.27	184.41	12195.66

- **Random Forest Regressor** give the lowest mae, mape, mse value

7. Prediction vs Actual for Random Forest Regressor (The best model)

In [69]:
```
test_df['y_true'] = y_test_raw
test_df['y_pred'] = rf_pred
test_df['year'] = 2015
```

In [70]:
```
test_df['datetime'] = pd.to_datetime(test_df[['year', 'month', 'day', 'h
our']])
test_df['zip_code'] = le.inverse_transform(test_df['zip_code_le'])
del test_df['zip_code_le']
```

In [71]:
```
test_df.tail()
```

Out[71]:

	month	day	weekday	hour	is_weekend	zip_code	y_true	y_pred	year	datetime
87015	1	31	5	23	1	10039	3	3.7	2015	2015-01-31 23:00:00
87016	1	31	5	23	1	11105	6	10.6	2015	2015-01-31 23:00:00
87017	1	31	5	23	1	11207	2	2.0	2015	2015-01-31 23:00:00
87018	1	31	5	23	1	10040	5	2.7	2015	2015-01-31 23:00:00
87019	1	31	5	23	1	11226	4	6.2	2015	2015-01-31 23:00:00

In [72]:
```
test_df = test_df.set_index('datetime')
```

In [73]:
```
test_df
```

Out[73]:

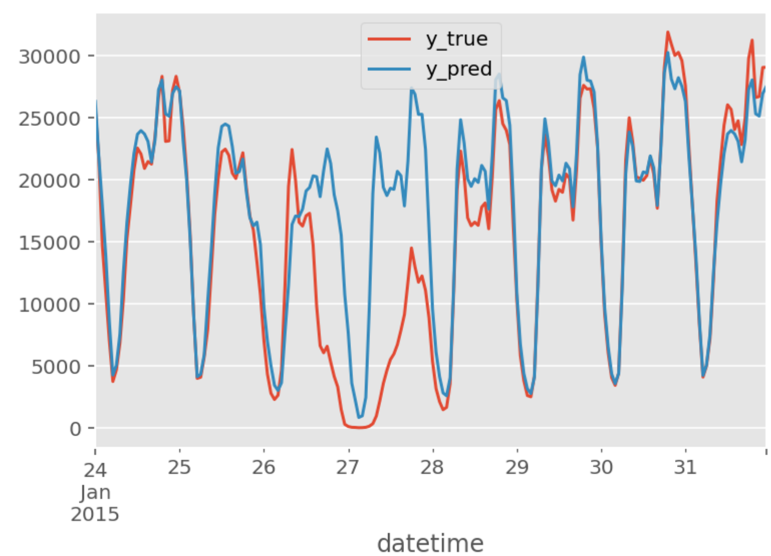
datetime	month	day	weekday	hour	is_weekend	zip_code	y_true	y_pred	year
2015-01-24 00:00:00	1	24	5	0	1	10280	26	27.0	2015
2015-01-24 00:00:00	1	24	5	0	1	10038	145	126.0	2015
2015-01-24 00:00:00	1	24	5	0	1	10004	88	88.2	2015
2015-01-24 00:00:00	1	24	5	0	1	10025	332	405.2	2015
2015-01-24 00:00:00	1	24	5	0	1	11217	91	124.0	2015
...	...	...	...	...	...	...	...	...	...
2015-01-31 23:00:00	1	31	5	23	1	10039	3	3.7	2015
2015-01-31 23:00:00	1	31	5	23	1	11105	6	10.6	2015
2015-01-31 23:00:00	1	31	5	23	1	11207	2	2.0	2015
2015-01-31 23:00:00	1	31	5	23	1	10040	5	2.7	2015
2015-01-31 23:00:00	1	31	5	23	1	11226	4	6.2	2015

21902 rows × 9 columns

By 'datetime'

In [74]:
```
test_df.groupby('datetime').sum()[['y_true', 'y_pred']].plot()
```

Out[74]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff87868bbb0>

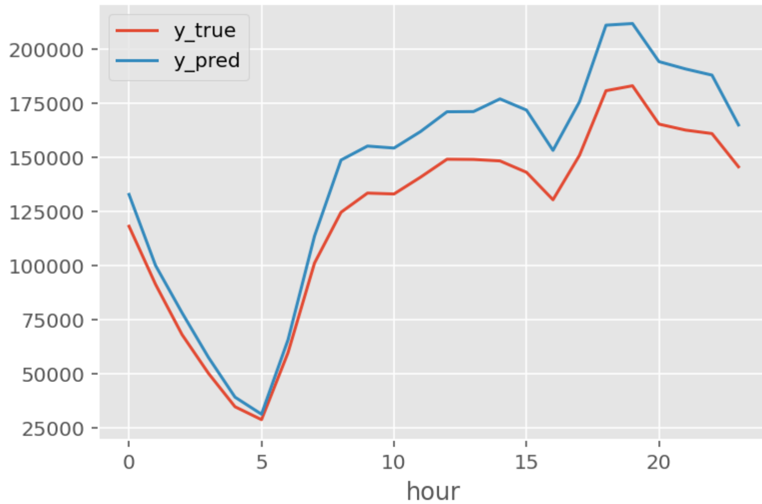


- The predictions are higher than actual values
- Failed to predict the demand when blizzard happened

By 'hour'

In [75]:
```
test_df[['hour','y_true', 'y_pred']].groupby('hour').sum()[['y_true', 'y_pred']].plot()
```

Out[75]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff8791a0af0>



- The predictions are similar to actual values during 00:00 - 07:00
- But higher after 07:00

8. Feature engineering

- add features with time

In [76]:
```
%%time
base_query = """
WITH base_data AS
(
  SELECT nyc_taxi.*, gis.* EXCEPT (zip_code_geom)
  FROM (
    SELECT *
    FROM `bigquery-public-data.new_york_taxi_trips.tlc_yellow_trips_2015
`
    WHERE
        EXTRACT(MONTH from pickup_datetime) = 1
        and pickup_latitude  <= 90 and pickup_latitude >= -90
    ) AS nyc_taxi
  JOIN (
    SELECT zip_code, state_code, state_name, city, county, zip_code_geom
    FROM `bigquery-public-data.geo_us_boundaries.zip_codes`
    WHERE state_code='NY'
    ) AS gis
  ON ST_CONTAINS(zip_code_geom, st_geogpoint(pickup_longitude, pickup_la
titude))
), distinct_datetime AS (

  SELECT distinct DATETIME_TRUNC(pickup_datetime, hour) as pickup_hour
  FROM base_data
), distinct_zip_code AS (

  SELECT distinct zip_code
  FROM base_data
), zip_code_datetime_join AS (

  SELECT
    *,
    EXTRACT(MONTH FROM pickup_hour) AS month,
    EXTRACT(DAY FROM pickup_hour) AS day,
    CAST(format_datetime('%u', pickup_hour) AS INT64) -1 AS weekday,
    EXTRACT(HOUR FROM pickup_hour) AS hour,
    CASE WHEN CAST(FORMAT_DATETIME('%u', pickup_hour) AS INT64) IN (6,
 7) THEN 1 ELSE 0 END AS is_weekend
  FROM distinct_zip_code
  CROSS JOIN distinct_datetime
), agg_data AS (

  SELECT
      zip_code,
      DATETIME_TRUNC(pickup_datetime, hour) as pickup_hour,
      COUNT(*) AS cnt
  FROM base_data
  GROUP BY zip_code, pickup_hour
), join_output AS (

  select
    zip_code_datetime.*,
    IFNULL(agg_data.cnt, 0) AS cnt
  from zip_code_datetime_join as zip_code_datetime
  LEFT JOIN agg_data
  ON zip_code_datetime.zip_code = agg_data.zip_code and zip_code_datetim
```

```
e.pickup_hour = agg_data.pickup_hour
)
SELECT
  *,
  LAG(cnt, 1) OVER(PARTITION BY zip_code ORDER BY pickup_hour) AS lag_1h_cnt,
  LAG(cnt, 24) OVER(PARTITION BY zip_code ORDER BY pickup_hour) AS lag_1d_cnt,
  LAG(cnt, 168) OVER(PARTITION BY zip_code ORDER BY pickup_hour) AS lag_7d_cnt,
  LAG(cnt, 336) OVER(PARTITION BY zip_code ORDER BY pickup_hour) AS lag_14d_cnt,
  ROUND(AVG(cnt) OVER(PARTITION BY zip_code ORDER BY pickup_hour ROWS BETWEEN 168 PRECEDING AND 1 PRECEDING), 2) AS avg_14d_cnt,
  ROUND(AVG(cnt) OVER(PARTITION BY zip_code ORDER BY pickup_hour ROWS BETWEEN 336 PRECEDING AND 1 PRECEDING), 2) AS avg_21d_cnt,
  CAST(STDDEV(cnt) OVER(PARTITION BY zip_code ORDER BY pickup_hour ROWS BETWEEN 168 PRECEDING AND 1 PRECEDING) AS INT64) AS std_14d_cnt,
  CAST(STDDEV(cnt) OVER(PARTITION BY zip_code ORDER BY pickup_hour ROWS BETWEEN 336 PRECEDING AND 1 PRECEDING) AS INT64) AS std_21d_cnt
FROM join_output
order by zip_code, pickup_hour
"""

base_df = pd.read_gbq(query=base_query, dialect='standard', project_id=PROJECT_ID)
```

```
INFO - pandas_gbq.gbq -   Elapsed 6.41 s. Waiting...
INFO - pandas_gbq.gbq -   Elapsed 7.76 s. Waiting...
INFO - pandas_gbq.gbq -   Elapsed 8.87 s. Waiting...
INFO - pandas_gbq.gbq -   Elapsed 9.99 s. Waiting...
INFO - pandas_gbq.gbq -   Elapsed 11.12 s. Waiting...
INFO - pandas_gbq.gbq -   Elapsed 12.26 s. Waiting...
INFO - pandas_gbq.gbq -   Elapsed 13.37 s. Waiting...
INFO - pandas_gbq.gbq -   Elapsed 14.6 s. Waiting...
INFO - pandas_gbq.gbq -   Elapsed 15.68 s. Waiting...
INFO - pandas_gbq.gbq -   Elapsed 16.76 s. Waiting...
Downloading: 100%|██████████| 278256/278256 [00:33<00:00, 8331.49rows/s]
INFO - pandas_gbq.gbq - Total time taken 51.8 s.
Finished at 2021-08-19 02:15:09.

CPU times: user 10.9 s, sys: 702 ms, total: 11.6 s
Wall time: 51.8 s
```

- features: one-hour lag, 24-hour lag, 168-hour lag

In [77]:
```
base_df.tail()
```

Out[77]:

	zip_code	pickup_hour	month	day	weekday	hour	is_weekend	cnt	lag_1h_cnt	lag_1(
278251	14801	2015-01-31 19:00:00	1	31	5	19	1	0	0.0	
278252	14801	2015-01-31 20:00:00	1	31	5	20	1	0	0.0	
278253	14801	2015-01-31 21:00:00	1	31	5	21	1	0	0.0	
278254	14801	2015-01-31 22:00:00	1	31	5	22	1	0	0.0	
278255	14801	2015-01-31 23:00:00	1	31	5	23	1	0	0.0	

In [78]:
```
le = LabelEncoder()
base_df['zip_code_le'] = le.fit_transform(base_df['zip_code'])
```

In [79]:
```
train_df, test_df = split_train_and_test(base_df, '2015-01-24')
```

In [80]:
```
train_df.tail()
```

Out[80]:

	zip_code	pickup_hour	month	day	weekday	hour	is_weekend	cnt	lag_1h_cnt	lag_1(
278059	14801	2015-01-23 19:00:00	1	23	4	19	0	0	0.0	
278060	14801	2015-01-23 20:00:00	1	23	4	20	0	0	0.0	
278061	14801	2015-01-23 21:00:00	1	23	4	21	0	0	0.0	
278062	14801	2015-01-23 22:00:00	1	23	4	22	0	0	0.0	
278063	14801	2015-01-23 23:00:00	1	23	4	23	0	0	0.0	

In [81]:
```
del train_df['zip_code']
del train_df['pickup_hour']
del test_df['zip_code']
del test_df['pickup_hour']
```

In [82]:
```
y_train_raw = train_df.pop('cnt')
y_test_raw = test_df.pop('cnt')
```

In [83]:
```
train_df = train_df.fillna(method='backfill')
test_df = test_df.fillna(method='backfill')
x_train = train_df.copy()
x_test = test_df.copy()
```

In [84]:
```
time_ex = Experiment('nyc-demand-prediction_time', interactive=True)
time_ex.observers.append(FileStorageObserver.create(experiment_dir))
```

Save Logger

In [85]:
```
@time_ex.config
def config():
    n_estimators=10
    n_jobs=-1
```

In [86]:
```
@time_ex.capture
def get_model(n_estimators, n_jobs):
    return RandomForestRegressor(n_estimators=n_estimators, n_jobs=n_job
s)
```

In [87]:
```
@time_ex.main
def run(_log, _run):
    global rf_reg, rf_pred
    rf_reg = get_model()
    rf_reg.fit(x_train, y_train_raw)
    rf_pred = rf_reg.predict(x_test)
    score = evaluation(y_test_raw, rf_pred)

    _run.log_scalar('model_name', rf_reg.__class__.__name__ + str('_tim
e'))
    _run.log_scalar('metrics', score.to_dict())

    return score.to_dict()
```

In [88]:
```
experiment_result = time_ex.run()
```

```
INFO - nyc-demand-prediction_time - Running command 'run'
INFO - nyc-demand-prediction_time - Started run with ID "10"
INFO - nyc-demand-prediction_time - Result: {'mape': {'score': nan}, 'm
ae': {'score': 6.686752172459893}, 'mse': {'score': 898.7883393215241}}
INFO - nyc-demand-prediction_time - Completed after 0:00:01
```

In [89]:
```
experiment_result.config
```

Out[89]:
```
{'n_estimators': 10, 'n_jobs': -1, 'seed': 791658605}
```

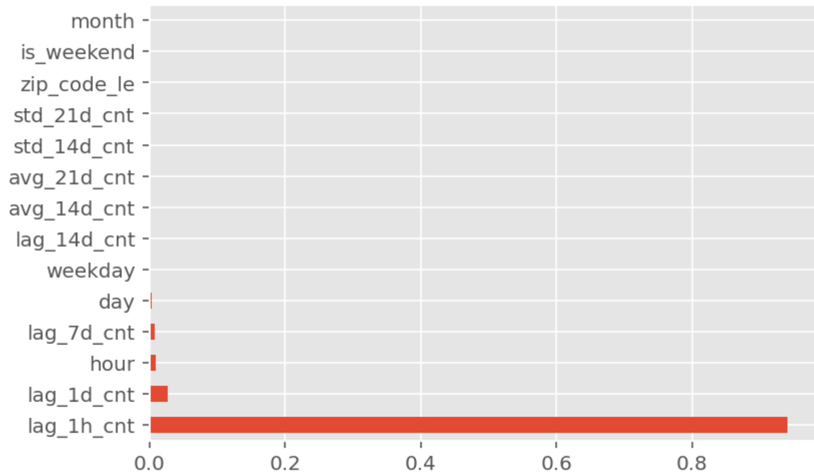
In [90]:
```
parsing_output(5)
```

Out[90]:

	model_name	experiment_num	config	mae	mape	mse
score	RandomForestRegressor_time	5	{'n_estimators': 10, 'n_jobs': -1, 'seed': 374...	6.94	NaN	1022.13

Coef significance

In [91]:
```
feat_importances = pd.Series(rf_reg.feature_importances_, index=x_train.
columns)
feat_importances.nlargest(15).plot(kind='barh');
```



RF without time feature vs RF with time feature

In [98]:
```
pd.concat([parsing_output(4), parsing_output(5)])
```

Out[98]:

	model_name	experiment_num	config	mae	mape	mse
score	RandomForestRegressor	4	{'n_estimators': 10, 'n_jobs': -1, 'seed': 682...	35.27	184.41	12195.66
score	RandomForestRegressor_time	5	{'n_estimators': 10, 'n_jobs': -1, 'seed': 374...	6.94	NaN	1022.13

- Compared the new RF model with the best model from last experiments
  - Our new RF model with 'time feature' gives lower mae and mse value
  - mape is 0 because true values from lag features are 0

9. Prediction vs Actual for RF with 'time' feature

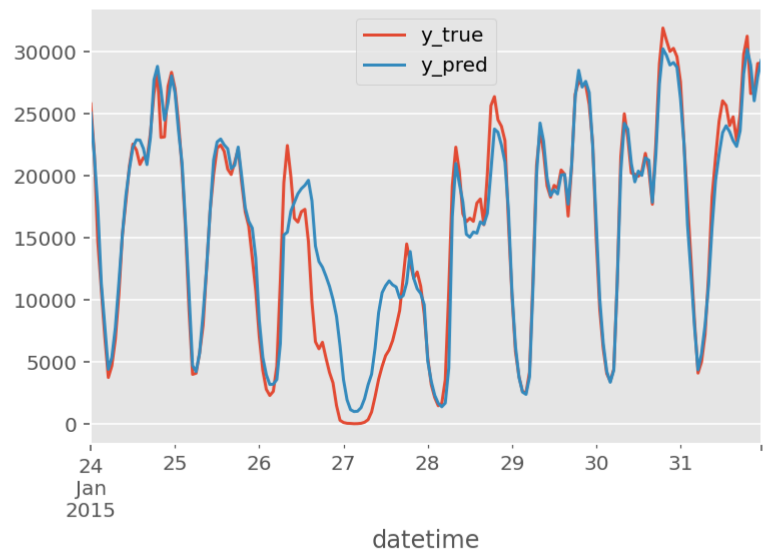
In [92]:
```
test_df['y_true'] = y_test_raw
test_df['y_pred'] = rf_pred
test_df['year'] = 2015
test_df['datetime'] = pd.to_datetime(test_df[['year', 'month', 'day', 'hour']])
test_df['zip_code'] = le.inverse_transform(test_df['zip_code_le'])
```

In [93]:
```
test_df = test_df.set_index('datetime')
```

By 'datetime'

In [94]:
```
test_df.groupby('datetime').sum()[['y_true', 'y_pred']].plot()
```

Out[94]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff878e45790>

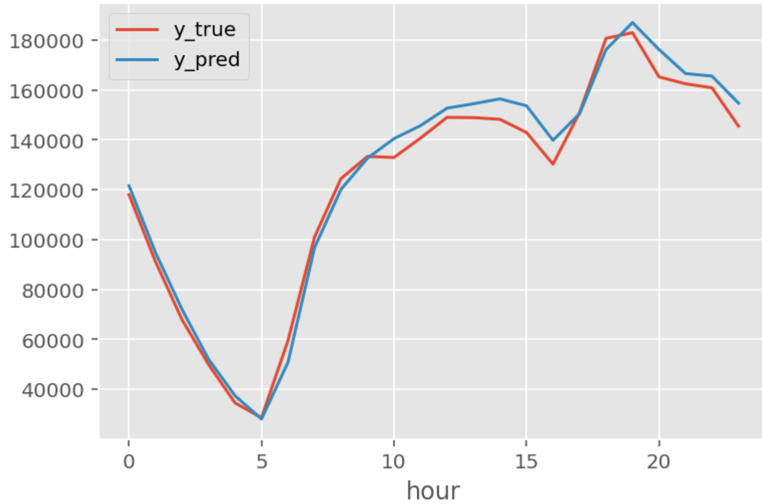


- It looks like our prediction is following the true value.
- The blizzard part is somewhat off but much better than before.

By 'hour'

In [96]:
```
test_df[['hour','y_true', 'y_pred']].groupby('hour').sum()[['y_true', 'y_pred']].plot()
```

Out[96]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff87a1e34c0>



- predict much better than last model