Predict Length of Stay (LoS) in ICU unit (regression)

predict LoS for ca 15k stays and train on ca 45k information ICU stays

data from [https://mimic.physionet.org/gettingstarted/access/ (https://mimic.physionet.org/gettingstarted/access/)](https://mimic.physionet.org/gettingstarted/access/)

Data merging

some datasets are quite big so pyspark and koalas were used initially for data merging (4 tables were used)

In [ ]:
```
import findspark
findspark.init()
from pyspark import SparkConf, SparkContext
conf = SparkConf().setMaster("local[*]").setAppName("LoS_ICU")
sc = SparkContext(conf = conf)
import databricks.koalas as ks
ks.set_option('compute.default_index_type','distributed') #use paralell computing
```

In [ ]:

```
events = ks.read_csv('EVENTS/EVENTS.csv.gz') # read events table number of row ca. 330M

events['CHARTTIME'] = ks.to_datetime(events['CHARTTIME']) #transform date information
events['STORETIME'] = ks.to_datetime(events['STORETIME'])
events['Date'] = events['CHARTTIME'].dt.date # select only the date part


#query the events table: take the averaged test results for each day and each patient
Avg24Hours_ITEMIDPerICUStayID = ks.sql('''
    SELECT ITEMID, avg(VALUENUM), VALUEUOM, SUBJECT_ID, ICUSTAY_ID, HADM_ID, Date
    FROM {table1}
    GROUP BY ITEMID, ICUSTAY_ID, VALUEUOM, Date, HADM_ID, SUBJECT_ID
    ORDER BY SUBJECT_ID ''', table1=events)

# len(Avg24Hours_ITEMIDPerICUStayID) # ca. 60M droped ca. 6x +/-

#query the previous + current total ICU stays for each single patient
nrICU_StaysPerSUBJ_ID=ks.sql('''
    SELECT SUBJECT_ID, COUNT(DISTINCT(ICUSTAY_ID)) as Total_ICU_Stays
    FROM {table1}
    GROUP BY SUBJECT_ID
    ORDER BY SUBJECT_ID ''', table1=events)

#merge the tw queries
EventsAvgAndMerged=Avg24Hours_ITEMIDPerICUStayID.merge(nrICU_StaysPerSUBJ_ID, on='SUBJECT_ID')

#read the admissions table (demographic information)
admissions = ks.read_csv('EVENTS/admissions.csv')

#query insurance plan, diagnosis at adimission, marital_status, ethnicity, etc...
DemographicsPerSUBJ_ID=ks.sql('''
    SELECT HADM_ID, ADMISSION_TYPE, ADMISSION_LOCATION, INSURANCE, LANGUAGE, RELIGION, MARITAL_STATUS, ETHNICITY, DIAG
NOSIS as DiagnosisAtAdmission
    FROM {table1} ''', table1=admissions)

#merge on the previous dataset
EventsAvgAndDemographMerged=EventsAvgAndMerged.merge(DemographicsPerSUBJ_ID, on='HADM_ID')

#read patients table
patients= ks.read_csv('EVENTS/PATIENTS.csv')
```

```
patients['DOB'] = ks.to_datetime(patients['DOB']).dt.date #transform data information and select only the date part

#query the table regarding gender and Date of Birth
DOBirthPerSUBJ_ID=ks.sql('''
    SELECT SUBJECT_ID, DOB as DateOfBirth, GENDER
    FROM {table1} ''', table1=patients)


#merge with the previous table on SUBJECT_ID
EventsAvgAndDemographMerged2=EventsAvgAndDemographMerged.merge(DOBirthPerSUBJ_ID, on='SUBJECT_ID')


#read the d_items table # information about the lables of the analysis performed on a patient
d_items= ks.read_csv('EVENTS/D_ITEMS.csv')

#query analysis labels
LabelPerITEM_ID=ks.sql('''
    SELECT ITEMID, LABEL as AnalysisType
    FROM {table1} ''', table1=d_items)

#merge with previous information
EventsAvgAndDemographMerged3=EventsAvgAndDemographMerged2.merge(LabelPerITEM_ID, on='ITEMID')


#read the icu_stays table to gather information on how long the patient stayed in ICU (our response variable to predic
t)
icu_stays = ks.read_csv('EVENTS/ICUSTAYS.csv')

#query the table
LoSPerICUSTAY_ID=ks.sql('''
    SELECT ICUSTAY_ID, LOS as Lenght_Stay
    FROM {table1} ''', table1=icu_stays)

#merge with previous information
data_Saved=EventsAvgAndDemographMerged3.merge(LoSPerICUSTAY_ID, on='ICUSTAY_ID')

data_Saved.to_csv('EVENTS/final', num_files=1) # save the results for further ananlysis

#sc.stop()
#ks.reset_option('compute.default_index_type')
```

In [2]:
```
data_Saved = ks.read_csv('EVENTS/final/final.csv')
```

In [4]:
```
data_Saved.columns
```

Out[4]:
```
Index(['ITEMID', 'avg(VALUENUM)', 'VALUEUOM', 'SUBJECT_ID', 'ICUSTAY_ID',
       'HADM_ID', 'Date', 'Total_ICU_Stays', 'ADMISSION_TYPE',
       'ADMISSION_LOCATION', 'INSURANCE', 'LANGUAGE', 'RELIGION',
       'MARITAL_STATUS', 'ETHNICITY', 'DiagnosisAtAdmission', 'DateOfBirth',
       'GENDER', 'AnalysisType', 'Lenght_Stay'],
      dtype='object')
```

In [5]:
```
data_Saved.isna().sum()
```

Out[5]:
```
ITEMID                         0
avg(VALUENUM)           35187052
VALUEUOM                45360401
SUBJECT_ID                     0
ICUSTAY_ID                     0
HADM_ID                        0
Date                           0
Total_ICU_Stays                0
ADMISSION_TYPE                 0
ADMISSION_LOCATION             0
INSURANCE                      0
LANGUAGE                25536623
RELIGION                  520413
MARITAL_STATUS          10038379
ETHNICITY                      0
DiagnosisAtAdmission         814
DateOfBirth                    0
GENDER                         0
AnalysisType                   0
Lenght_Stay                    0
dtype: int64
```

In [6]:
```
len(data_Saved) #60 million rows! #chart events has 330 million rows!
```

Out[6]:
```
59319892
```

In [3]:
```
data_Saved.head(50)
```

Out[3]:

	ITEMID	avg(VALUENUM)	VALUEUOM	SUBJECT_ID	ICUSTAY_ID	HADM_ID	Date	Total_ICU_Stays	ADMISSION_TYPE	ADMISSION_LOCATION
0	85	NaN	None	148	227964	199488	2107-09-10	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
1	128	NaN	None	148	227964	199488	2107-09-21	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
2	184	1.000000	None	148	227964	199488	2107-09-11	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
3	202	NaN	None	148	227964	199488	2107-09-17	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
4	207	NaN	None	148	227964	199488	2107-09-18	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
5	478	NaN	None	148	227964	199488	2107-09-21	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
6	617	NaN	None	148	227964	199488	2107-09-16	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
7	640	NaN	None	148	227964	199488	2107-09-21	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
8	677	35.879634	Deg. C	148	227964	199488	2107-09-22	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
9	779	144.000000	mmHg	148	227964	199488	2107-09-08	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
10	798	1.000000	None	148	227964	199488	2107-09-10	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
11	824	14.550000	None	148	227964	199488	2107-09-10	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
12	833	2.645000	/mic l	148	227964	199488	2107-09-19	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
13	1517	NaN	None	148	227964	199488	2107-09-08	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
14	1530	1.400000	None	148	227964	199488	2107-09-15	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
15	1535	4.600000	None	148	227964	199488	2107-09-10	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM

	ITEMID	avg(VALUENUM)	VALUEUOM	SUBJECT_ID	ICUSTAY_ID	HADM_ID	Date	Total_ICU_Stays	ADMISSION_TYPE	ADMISSION_LOCATION
16	8547	155.000000	mmHg	148	227964	199488	2107-09-22	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
17	32	NaN	None	148	227964	199488	2107-09-15	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
18	136	NaN	None	148	227964	199488	2107-09-09	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
19	200	NaN	None	148	227964	199488	2107-09-13	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
20	425	NaN	None	148	227964	199488	2107-09-08	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
21	674	NaN	None	148	227964	199488	2107-09-21	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
22	677	37.137040	Deg. C	148	227964	199488	2107-09-19	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
23	722	NaN	None	148	227964	199488	2107-09-17	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
24	1523	108.000000	None	148	227964	199488	2107-09-13	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
25	5817	85.000000	mmHg	148	227964	199488	2107-09-14	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
26	8377	NaN	None	148	227964	199488	2107-09-22	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
27	8480	NaN	None	148	227964	199488	2107-09-21	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
28	8488	NaN	None	148	227964	199488	2107-09-20	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
29	39	NaN	None	148	227964	199488	2107-09-16	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
30	40	NaN	None	148	227964	199488	2107-09-08	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
31	199	NaN	None	148	227964	199488	2107-09-21	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
32	210	NaN	None	148	227964	199488	2107-09-21	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM

	ITEMID	avg(VALUENUM)	VALUEUOM	SUBJECT_ID	ICUSTAY_ID	HADM_ID	Date	Total_ICU_Stays	ADMISSION_TYPE	ADMISSION_LOCATION
33	218	46.000000	cmH2O	148	227964	199488	2107-09-09	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
34	283	NaN	None	148	227964	199488	2107-09-18	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
35	284	NaN	None	148	227964	199488	2107-09-17	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
36	294	NaN	None	148	227964	199488	2107-09-17	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
37	444	10.166667	cmH2O	148	227964	199488	2107-09-17	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
38	547	NaN	None	148	227964	199488	2107-09-22	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
39	617	NaN	None	148	227964	199488	2107-09-23	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
40	645	NaN	None	148	227964	199488	2107-09-11	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
41	646	93.807692	%	148	227964	199488	2107-09-09	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
42	680	NaN	None	148	227964	199488	2107-09-08	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
43	706	NaN	None	148	227964	199488	2107-09-11	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
44	779	85.000000	mmHg	148	227964	199488	2107-09-14	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
45	787	29.000000	None	148	227964	199488	2107-09-22	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
46	791	1.000000	None	148	227964	199488	2107-09-10	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
47	837	149.000000	None	148	227964	199488	2107-09-21	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
48	1427	NaN	None	148	227964	199488	2107-09-17	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM
49	1532	2.000000	None	148	227964	199488	2107-09-21	1	EMERGENCY	TRANSFER FROM HOSP/EXTRAM

In [5]:
```
analysis=data_Saved.AnalysisType.unique()
```

In [7]:
```
len(analysis) #6200 analysis types aka kind of 6000 columns!
```

Out[7]: 6196

In [26]:
```
data_Saved=data_Saved.rename(columns={"avg(VALUENUM)": "DailyAverage"})
```

In [35]:
```
#SELECT ONLY information for the first day in ICU
#we want to predict LoS at nearly the begining of patient admission in ICU...
#MIN(DATE) allows only information of the first day of information
DataPerICU_Stay_First24h = ks.sql('''SELECT MIN(Date), avg(DailyAverage), SUBJECT_ID, ICUSTAY_ID,
                                     HADM_ID, first(Total_ICU_Stays), first(ADMISSION_TYPE), first(ADMISSION_LOCATIO
N),
                                     first(INSURANCE), first(LANGUAGE), first(RELIGION),
                                     first(MARITAL_STATUS), first(ETHNICITY), first(DiagnosisAtAdmission), first(DateO
fBirth),
                                     first(GENDER), AnalysisType, first(Lenght_Stay)
                                     FROM {table1}
                                     GROUP BY ICUSTAY_ID, SUBJECT_ID, HADM_ID, AnalysisType''', table1=data_Saved)
```

In [36]:
```
len(DataPerICU_Stay_First24h) # 14 million rows!
```

Out[36]: 14051986

In [37]:
```
len(DataPerICU_Stay_First24h.SUBJECT_ID.unique()) #46 000 patients
```

Out[37]: 46438

In [12]:
```
len(DataPerICU_Stay_First24h.ICUSTAY_ID.unique()) #61 000 icu admissions #  alot with more than 1 admission ca. 20k
```

Out[12]: 60840

In [34]:
```
len(DataPerICU_Stay_First24h[DataPerICU_Stay_First24h['first(Total_ICU_Stays)'] > 1])
```

Out[34]: 22961

In [39]:
```
DataPerICU_Stay_First24h.head()
```

Out[39]:

	min(Date)	avg(DailyAverage)	SUBJECT_ID	ICUSTAY_ID	HADM_ID	first(Total_ICU_Stays)	first(ADMISSION_TYPE)	first(ADMISSION_LOCATION)
0	2181-11-26	NaN	55973	200001	152234	14	EMERGENCY	CLINIC REFERRAL/PREMATURE
1	2181-11-26	98.666667	55973	200001	152234	14	EMERGENCY	CLINIC REFERRAL/PREMATURE
2	2181-11-25	NaN	55973	200001	152234	14	EMERGENCY	CLINIC REFERRAL/PREMATURE
3	2199-08-07	NaN	27513	200003	163557	1	EMERGENCY	PHYS REFERRAL/NORMAL DELI
4	2199-08-03	4.570000	27513	200003	163557	1	EMERGENCY	PHYS REFERRAL/NORMAL DELI

In [42]:
```
# convert DOB to data first
DataPerICU_Stay_First24h['first(DateOfBirth)']=ks.to_datetime(DataPerICU_Stay_First24h['first(DateOfBirth)']).dt.date
#calculate age of patient at admission (just using years...)
DataPerICU_Stay_First24h['Age']=DataPerICU_Stay_First24h['min(Date)'].dt.year - DataPerICU_Stay_First24h['first(DateOf
Birth)'].dt.year
```

```
c:\spark\python\pyspark\sql\pandas\functions.py:383: UserWarning: In Python 3.6+ and Spark 3.0+, it is preferred to s
pecify type hints for pandas UDF instead of specifying pandas UDF type which will be deprecated in the future release
s. See SPARK-28264 for more details.
  warnings.warn(
```

In [44]:
```
DataPerICU_Stay_First24h['Age'].describe() #people older than 89 are stated as 300 years old at admission due to claim
ed ethics issues
```

Out[44]:
```
count    1.405199e+07
mean     6.893595e+01
std      5.360414e+01
min      0.000000e+00
25%      5.000000e+01
50%      6.400000e+01
75%      7.700000e+01
max      3.110000e+02
Name: Age, dtype: float64
```

In [48]:
```
#dataset holders provided the median information for the 89 and older population
DataPerICU_Stay_First24h['Age'].loc[DataPerICU_Stay_First24h['Age']  > 89] = 91.4 #replace with the median age
```

In [49]:
```
DataPerICU_Stay_First24h['Age'].describe() #OK
```

Out[49]:
```
count    1.405199e+07
mean     6.000129e+01
std      2.287624e+01
min      0.000000e+00
25%      5.000000e+01
50%      6.400000e+01
75%      7.700000e+01
max      9.140000e+01
Name: Age, dtype: float64
```

In [59]:
```
DataPerICU_Stay_First24h['AnalysisType']= DataPerICU_Stay_First24h['AnalysisType'].str.lower() #all to lower case
DataPerICU_Stay_First24h['AnalysisType'] = DataPerICU_Stay_First24h['AnalysisType'].str.replace(" ","_") #replace spac
e for '_'
```

In [62]:
```
DataPerICU_Stay_First24h['avg(DailyAverage)'].describe()
```

Out[62]:
```
count    6.124011e+06
mean     6.934117e+01
std      2.020131e+03
min     -6.000000e+02
25%      1.919080e+00
50%      1.200000e+01
75%      6.900000e+01
max      4.154509e+06
Name: avg(DailyAverage), dtype: float64
```

In [ ]:
```
#pivot the table to have information about anaylsis results per ICUSTAY_ID
PivotTable= DataPerICU_Stay_First24h.pivot(index='ICUSTAY_ID', columns='AnalysisType', values='avg(DailyAverage)')
PivotTable=PivotTable.reset_index()

# we wont need this information: Analysis and dau«ily average has been pivoted
PivotTable=PivotTable.drop(['AnalysisType', 'avg(DailyAverage)', 'min(Date)', 'first(DateOfBirth)'])
PivotTable=PivotTable.drop_duplicates()


#save for further analysis
DataPerICU_Stay_First24h.to_csv('EVENTS/DataPerICU_Stay_First24h_2', num_files=1)
PivotTable.to_csv('EVENTS/pivot_2', num_files=1)
```

In [ ]:
```
#sc.stop()
```

Use Pandas once file sizes are now much smaller

In [4]:
```
import pandas as pd
```

In [44]:
```
PivotTable = pd.read_csv('EVENTS/pivot_2/pivot_2.csv')
```

In [13]:
```
PivotTable.isna().sum()
```

```
Out[13]: #1_chest_tube_irrig.                     60840
         %_inspir._time                           60840
         %cool_mist                               60839
         (l)_fem_art                              60840
         (r)_fem_art                              60840
         (r)_femoral_sheath                       60839
         (r)_nephrostomy                          60840
         .45%ns                                   60840
         02_analyzed                              60839
         02_tubing_present                        60840
         1-10_ml_20%_mucomyst                     60840
         1._nausea_and_vomit.                     60839
         1.nausea_&vomitting                      60839
         10%_alcohol/_cc/hr                       60839
         10%_alcohol_cc/hr                        60839
         10%_etoh_cc/hr                           60839
         10%alcohl                                60839
         10_min                                   60840
         14_g_infiltration_scale                  60840
         14_g_phlebitis_scale                     60840
         14_gauge_dressing_occlusive              60411
         14_gauge_placed_in_outside_facility      60420
         14_gauge_placed_in_the_field             60630
         14_gauge_reason_discontinued             60840
         14_gauge_site_appear                     60840
         16_g_infiltration_scale                  60840
         16_g_phlebitis_scale                     60840
         16_gauge_dressing_occlusive              56284
         16_gauge_placed_in_outside_facility      56331
         16_gauge_placed_in_the_field             58044
                                                  ...
         xigris__mg/hour                          60839
         xigris_cc/hr                             60838
         xigris_mcg/kg/hr                         60833
         xigris_mg/hr                             60835
         xygris                                   60837
         xylocaine_2%_jelly                       60840
         yawning                                  60702
         yi_mv                                    60839
         zantac                                   60840
         zantac(ranitidine)                       60840
```

```
zantac_pg                          60840
zantc                              60840
zidovudine/azt                     60840
zosyn                              60840
zygris                             60839
zz_equip_functioning               60840
zz_tubing_present                  60840
zzg_and_mask_present               60840
zzo2av                             57651
zzo2avi                            57669
zzz_stim_thresh_ma_[unit]          60840
zzz_stim_thresh_ma_[value]         60830
zzzgth___calc___(cm)               60813
zzzly_wake_up                      60840
zzzn_management                    60840
zzzph                              60840
zzzt_stim_thresh_ma_[unit]         60840
zzzt_stim_thresh_ma_[value]        60833
zzzzth_in_centimeter               60813
zzzzuent_press_mmhg                60839
Length: 5342, dtype: int64
```

In [7]:
```
PivotTable.shape
```

Out[7]:
```
(60840, 2395)
```

In [50]:

```
PivotTable.isna().sum()
```

Out[50]:

```
14_gauge_dressing_occlusive               61364
14_gauge_placed_in_outside_facility       61373
14_gauge_placed_in_the_field              61584
16_gauge_dressing_occlusive               57193
16_gauge_placed_in_outside_facility       57242
16_gauge_placed_in_the_field              58977
18_gauge_dressing_occlusive               48478
18_gauge_placed_in_outside_facility       48574
18_gauge_placed_in_the_field              53661
20_gauge_dressing_occlusive               46054
20_gauge_placed_in_outside_facility       46150
20_gauge_placed_in_the_field              52258
22_gauge_dressing_occlusive               56835
22_gauge_placed_in_outside_facility       56901
22_gauge_placed_in_the_field              58773
3%_ns                                     61794
aado2                                     60554
aado2apacheiivalue                        61788
abd_girth                                 61793
abdominal_changes:_observation            61657
abdominal_girth                           61769
abdominal_girth_(cm)                      58249
abg_chloirde                              61742
abg_chloride                              61748
abg_hct                                   61584
abg_potassium                             61711
abg_sodium                                61758
abi_(l)                                   61650
abi_(r)                                   61647
abi_ankle_bp_[left]                       61650
                                          ...
wbcscore_apacheiv                         61787
weight_change                             46779
weight_change__(gms)                      57768
weight_kg                                 60793
whitebloodc_4.0-11.0                      55807
working_pressure                          60611
xigris                                    61775
xigris_cc/hr                              61793
xigris_mcg/kg/hr                          61789
xigris_mg/hr                              61791
```

```
xygris                                  61793
yawning                                 61657
zzo2av                                  58535
zzo2avi                                 58556
zzz_stim_thresh_ma_[value]              61786
zzzgth___calc___(cm)                    61762
zzzt_stim_thresh_ma_[value]             61789
zzzzth_in_centimeter                    61762
first(Total_ICU_Stays)                      0
first(ADMISSION_TYPE)                       0
first(ADMISSION_LOCATION)                   0
first(INSURANCE)                            0
first(LANGUAGE)                         26228
first(RELIGION)                           482
first(MARITAL_STATUS)                   10456
first(ETHNICITY)                            0
first(DiagnosisAtAdmission)                 2
first(GENDER)                               0
first(Lenght_Stay)                          0
Age                                         0
Length: 1594, dtype: int64
```

In [45]:
```
PivotTable=PivotTable.dropna(axis=1, thresh=2) # keep columns that have at least 2 non-NANs
```

In [6]:
```
PivotTable.head()
```

Out[6]:

	ICUSTAY_ID	14_gauge_dressing_occlusive	14_gauge_placed_in_outside_facility	14_gauge_placed_in_the_field	16_gauge_dressing_occlusive	16_
0	200166	NaN	NaN	NaN	NaN	
1	200379	NaN	NaN	NaN	NaN	
2	200625	NaN	NaN	NaN	NaN	
3	200718	NaN	NaN	NaN	NaN	
4	201031	NaN	NaN	NaN	NaN	

5 rows × 1583 columns

In [9]:
```
PivotTable.shape
```

Out[9]: (60840, 1583)

In [46]:
```
ICU_Stay_Info = pd.read_csv('EVENTS/DataPerICU_Stay_First24h_2/24h_2.csv')
```

In [11]:
```
ICU_Stay_Info.shape
```

Out[11]: (61796, 15)

In [9]:
```
ICU_Stay_Info.head()
```

Out[9]:

	SUBJECT_ID	ICUSTAY_ID	HADM_ID	first(Total_ICU_Stays)	first(ADMISSION_TYPE)	first(ADMISSION_LOCATION)	first(INSURANCE)	first(LANGU
0	491	235261	157083	1	EMERGENCY	EMERGENCY ROOM ADMIT	Medicare	
1	507	264188	136251	2	ELECTIVE	PHYS REFERRAL/NORMAL DELI	Medicare	
2	518	232791	153168	9	EMERGENCY	EMERGENCY ROOM ADMIT	Private	I
3	975	299931	165225	6	EMERGENCY	EMERGENCY ROOM ADMIT	Medicare	I
4	1162	278191	100147	1	EMERGENCY	EMERGENCY ROOM ADMIT	Private	

In [47]:
```
#merge with addition information on the the first 24h previously saved
PivotTable=PivotTable.merge(ICU_Stay_Info, left_on=PivotTable['ICUSTAY_ID'], right_on= ICU_Stay_Info['ICUSTAY_ID'])
```

In [19]:
```
PivotTable.head()
```

Out[19]:

	14_gauge_dressing_occlusive	14_gauge_placed_in_outside_facility	14_gauge_placed_in_the_field	16_gauge_dressing_occlusive	16_gauge_placed_
0	NaN	NaN	NaN	NaN	
1	NaN	NaN	NaN	NaN	
2	NaN	NaN	NaN	NaN	
3	NaN	NaN	NaN	NaN	
4	NaN	NaN	NaN	NaN	

5 rows × 1595 columns

In [48]:
```
#drop non-relevant columns
PivotTable=PivotTable.drop(['key_0', 'ICUSTAY_ID_x', 'ICUSTAY_ID_y', 'HADM_ID', 'SUBJECT_ID'], axis=1)
```

In [14]:
```
PivotTable.shape # king of 1600 features!!
```

Out[14]:
```
(61796, 1595)
```

In [20]:
```
PivotTable.isna().sum(axis=1)
```

Out[20]:
```
0        1467
1        1494
2        1477
3        1519
4        1515
5        1434
6        1495
7        1443
8        1490
9        1415
10       1430
11       1521
12       1439
13       1478
14       1442
15       1437
16       1487
17       1479
18       1492
19       1470
20       1482
21       1517
22       1508
23       1431
24       1512
25       1445
26       1454
27       1507
28       1417
29       1540
         ...
61766    1470
61767    1518
61768    1437
61769    1548
61770    1460
61771    1441
61772    1556
61773    1475
61774    1525
61775    1537
```

```
61776    1478
61777    1530
61778    1439
61779    1557
61780    1561
61781    1513
61782    1480
61783    1567
61784    1562
61785    1518
61786    1528
61787    1564
61788    1562
61789    1552
61790    1567
61791    1572
61792    1584
61793    1570
61794    1563
61795    1584
Length: 61796, dtype: int64
```

In [22]:
```
# replace special charcters on columns names that might mess with modeling
PivotTable.columns = PivotTable.columns.str.replace('[.,%,#,@,&,[,],/,-]', '')
```

In [49]:
```
PivotTable.columns
```

Out[49]:
```
Index(['14_gauge_dressing_occlusive', '14_gauge_placed_in_outside_facility',
       '14_gauge_placed_in_the_field', '16_gauge_dressing_occlusive',
       '16_gauge_placed_in_outside_facility', '16_gauge_placed_in_the_field',
       '18_gauge_dressing_occlusive', '18_gauge_placed_in_outside_facility',
       '18_gauge_placed_in_the_field', '20_gauge_dressing_occlusive',
       ...
       'first(ADMISSION_LOCATION)', 'first(INSURANCE)', 'first(LANGUAGE)',
       'first(RELIGION)', 'first(MARITAL_STATUS)', 'first(ETHNICITY)',
       'first(DiagnosisAtAdmission)', 'first(GENDER)', 'first(Lenght_Stay)',
       'Age'],
      dtype='object', length=1594)
```

LightGBM Model

In [51]:
```
#split in train and test sets
from sklearn.model_selection import train_test_split
LoS, LoS_test = train_test_split(PivotTable, test_size=0.30, random_state=42) # 30% for test
```

In [39]:
```
LoS.dtypes
```

```
Out[39]: 14_gauge_dressing_occlusive                float64
         14_gauge_placed_in_outside_facility        float64
         14_gauge_placed_in_the_field               float64
         16_gauge_dressing_occlusive                float64
         16_gauge_placed_in_outside_facility        float64
         16_gauge_placed_in_the_field               float64
         18_gauge_dressing_occlusive                float64
         18_gauge_placed_in_outside_facility        float64
         18_gauge_placed_in_the_field               float64
         20_gauge_dressing_occlusive                float64
         20_gauge_placed_in_outside_facility        float64
         20_gauge_placed_in_the_field               float64
         22_gauge_dressing_occlusive                float64
         22_gauge_placed_in_outside_facility        float64
         22_gauge_placed_in_the_field               float64
         3_ns                                       float64
         aado2                                      float64
         aado2apacheiivalue                         float64
         abd_girth                                  float64
         abdominal_changes:_observation             float64
         abdominal_girth                            float64
         abdominal_girth_(cm)                       float64
         abg_chloirde                               float64
         abg_chloride                               float64
         abg_hct                                    float64
         abg_potassium                              float64
         abg_sodium                                 float64
         abi_(l)                                    float64
         abi_(r)                                    float64
         abi_ankle_bp_[left]                        float64
                                                     ...
         weight_change                              float64
         weight_change__(gms)                       float64
         weight_kg                                  float64
         whitebloodc_40110                          float64
         working_pressure                           float64
         xigris                                     float64
         xigris_cchr                                float64
         xigris_mcgkghr                             float64
         xigris_mghr                                float64
         xygris                                     float64
```

```
yawning                                  float64
zzo2av                                   float64
zzo2avi                                  float64
zzz_stim_thresh_ma_[value]               float64
zzzgth___calc___(cm)                     float64
zzzt_stim_thresh_ma_[value]              float64
zzzzth_in_centimeter                     float64
ICUSTAY_ID_y                               int64
first(Total_ICU_Stays)                     int64
first(ADMISSION_TYPE)                     object
first(ADMISSION_LOCATION)                 object
first(INSURANCE)                          object
first(LANGUAGE)                           object
first(RELIGION)                           object
first(MARITAL_STATUS)                     object
first(ETHNICITY)                          object
first(DiagnosisAtAdmission)               object
first(GENDER)                             object
first(Lenght_Stay)                       float64
Age                                      float64
Length: 1595, dtype: object
```

In [53]:

```
LoS.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 43257 entries, 5647 to 56422
Columns: 1594 entries, 14_gauge_dressing_occlusive to Age
dtypes: category(9), float64(1584), int64(1)
memory usage: 524.2 MB
```

In [52]:

```
#transform object variables into category type for LGBM
for c in LoS.columns:
    col_type = LoS[c].dtypes
    if (col_type == object):
        LoS[c] = LoS[c].astype('category')

for c in LoS_test.columns:
    col_type = LoS_test[c].dtypes
    if (col_type == object):
        LoS_test[c] = LoS_test[c].astype('category')
```

```
C:\Users\lucia\Anaconda3\lib\site-packages\ipykernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-
copy
  """
C:\Users\lucia\Anaconda3\lib\site-packages\ipykernel_launcher.py:10: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#indexing-view-versus-
copy
  # Remove the CWD from sys.path while we load stuff.
```

In [165]:

```
# spli feature and response variables for train and test sets
y_train=LoS['first(Lenght_Stay)']
X_train=LoS.drop('first(Lenght_Stay)', axis=1 )
y_test=LoS_test['first(Lenght_Stay)']
X_test=LoS_test.drop('first(Lenght_Stay)', axis=1 )
```

In [166]:
```
#transform object variables into categgory type for LGBM
for c in X_train.columns:
    col_type = X_train[c].dtype
    if col_type == 'object':
        X_train[c] = X_train[c].astype('category')

for c in X_test.columns:
    col_type = X_test[c].dtype
    if col_type == 'object':
        X_test[c] = X_test[c].astype('category')
```

In [167]:
```
#it requires further repalcement of special charcters on columns names that might mess with LGBM
X_train.columns = X_train.columns.str.replace('(', '').str.replace(')', '').str.replace('<', '').str.replace('#', '').
str.replace('%', '').str.replace('[', '').str.replace(']', '').str.replace('-', '').str.replace('/', '').str.replace(
'>', '').str.replace('.', '')
X_test.columns = X_test.columns.str.replace('(', '').str.replace(')', '').str.replace('<', '').str.replace('#', '').st
r.replace('%', '').str.replace('[', '').str.replace(']', '').str.replace('-', '').str.replace('/', '').str.replace('>'
, '').str.replace('.', '')
```

In [168]:
```
import re  # transform from json to not cause problems in lightbgm due to special json characters in column names
X_train = X_train.rename(columns = lambda x:re.sub('[^A-Za-z0-9_]+', '', x))
X_test = X_test.rename(columns = lambda x:re.sub('[^A-Za-z0-9_]+', '', x))
```

In [132]:
```
#according to dataset manager some analysis may contain misspelling and not uniform information about analysis but it
 is a open
# free character introduction describing the analysis performed
# string match was performed in order to merge columns that most probably refer to the same analysis type
import difflib
matches=dict()

for c in X_train.columns:
    matches[c]= difflib.get_close_matches(c, X_train.columns, cutoff = 0.70, n = 15)
```

In [134]:
```
matches['22_gauge_placed_in_outside_facility']
```

Out[134]:
```
['22_gauge_placed_in_outside_facility',
 '20_gauge_placed_in_outside_facility',
 '18_gauge_placed_in_outside_facility',
 '16_gauge_placed_in_outside_facility',
 '14_gauge_placed_in_outside_facility',
 'iabp_placed_in_outside_facility',
 'cco_pac_placed_in_outside_facility',
 'ric_placed_in_outside_facility',
 'icp_line_placed_in_outside_facility',
 'ava_line_placed_in_outside_facility',
 'sheath_placed_in_outside_facility',
 'trauma_line_placed_in_outside_facility',
 'picc_line_placed_in_outside_facility',
 'midline_placed_in_outside_facility',
 'pa_catheter_placed_in_outside_facility']
```

In [1]:
```
#replace values for the mean in the most similar analysis type # this will replace a lot of NaN

for similars in matches.values():
    average1=X_train[similars].mean(axis=1)
    average2=X_test[similars].mean(axis=1)
    X_train[similars]= X_train[similars].T.fillna(average1).T
    X_test[similars]= X_test[similars].T.fillna(average2).T
```

In [170]:
```
X_train.head()
```

Out[170]:

	14_gauge_dressing_occlusive	14_gauge_placed_in_outside_facility	14_gauge_placed_in_the_field	16_gauge_dressing_occlusive	16_gauge_pla
5647	1.0	0.0	0.000000	1.0	
49026	NaN	NaN	NaN	NaN	
6112	1.0	1.0	0.833333	1.0	
45879	NaN	NaN	NaN	NaN	
60640	1.0	0.0	0.000000	1.0	

5 rows × 1593 columns

In [172]:
```
X_train.shape
```

Out[172]:
```
(43257, 1593)
```

In [181]:
```
#drop duplicated columns

X_train = X_train.loc[:,~X_train.columns.duplicated()]
X_test = X_test.loc[:,~X_test.columns.duplicated()]
```

In [182]:
```
X_train.shape
```

Out[182]:
```
(43257, 1560)
```

In [20]:
```
import lightgbm as lgb #pip install lightgbm

clf = lgb.LGBMRegressor(boosting_type='gbdt', objective='regression', n_jobs=-1,
                              metric= 'l2', subsample = 0.8 , force_col_wise = True,
                             learning_rate= 0.1, colsample_bytree= 0.2, reg_alpha= 3, reg_lambda= 1,
                             n_estimators=5000, max_depth=-1, num_leaves=100 )
```

In [183]:
```
#fit the lghbm model
clf.fit(X_train, y_train, early_stopping_rounds= 30, eval_metric= 'l2', #mean squared error
                            eval_set= [(X_test,y_test)], eval_names= ['test'], verbose= 100, feature_name= 'auto', cat
egorical_feature= 'auto')
```

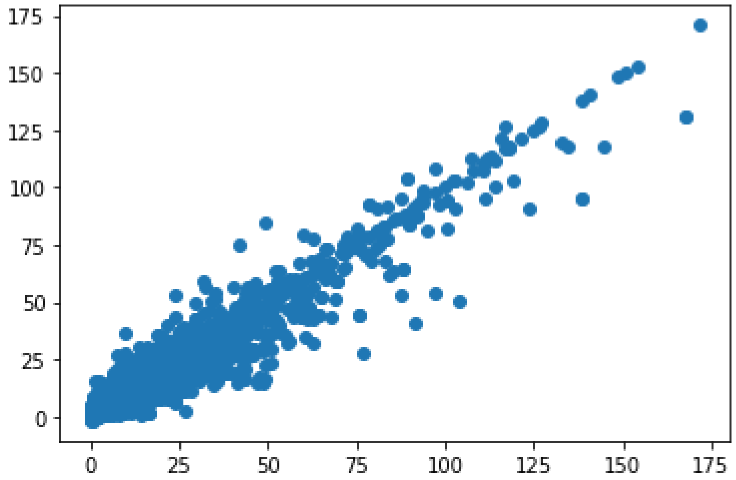
```
C:\Users\lucia\Anaconda3\lib\site-packages\lightgbm\basic.py:1286: UserWarning: Overriding the parameters from Refere
nce Dataset.
  warnings.warn('Overriding the parameters from Reference Dataset.')
C:\Users\lucia\Anaconda3\lib\site-packages\lightgbm\basic.py:1098: UserWarning: categorical_column in param dict is o
verridden.
  warnings.warn('{} in param dict is overridden.'.format(cat_alias))

Training until validation scores don't improve for 30 rounds
[100]	test's l2: 8.2747
[200]	test's l2: 7.72796
[300]	test's l2: 7.56052
[400]	test's l2: 7.50668
[500]	test's l2: 7.4783
[600]	test's l2: 7.45319
[700]	test's l2: 7.44262
[800]	test's l2: 7.43858
[900]	test's l2: 7.43164
[1000]	test's l2: 7.42564
[1100]	test's l2: 7.42306
[1200]	test's l2: 7.42138
Early stopping, best iteration is:
[1265]	test's l2: 7.41953
```

Out[183]:
```
LGBMRegressor(colsample_bytree=0.2, force_col_wise=True, metric='l2',
              n_estimators=5000, num_leaves=100, objective='regression',
              reg_alpha=3, reg_lambda=1, subsample=0.8)
```

In [184]:
```
#predict LoS for test
LoS_hat=clf.predict(X_test) #LoS is in days
```

In [186]:
```
from matplotlib import pyplot as plt
plt.scatter(y_test, LoS_hat) # not bad! it is quite a linear diagonal centered line as expected
```

Out[186]: <matplotlib.collections.PathCollection at 0x1aea10ec4c8>



In [190]:
```
y_test.median()
```

Out[190]: 2.0881

In [197]:
```
clf_2 = lgb.LGBMRegressor(boosting_type='gbdt', objective='regression', n_jobs=-1,
                               metric= 'l2_root', subsample = 0.8 , force_col_wise = True,
                              learning_rate= 0.01, colsample_bytree= 0.2, reg_alpha= 3, reg_lambda= 1,
                              n_estimators=20000, max_depth=-1, num_leaves=100 )

#fit the lghbm model
clf_2.fit(X_train, y_train, early_stopping_rounds= 30, eval_metric= 'l2_root', #root mean squared error
                            eval_set= [(X_test,y_test)], eval_names= ['test'], verbose= 1000, feature_name= 'auto', ca
tegorical_feature= 'auto')
```

```
Training until validation scores don't improve for 30 rounds
[1000]  test's rmse: 2.79971
[2000]  test's rmse: 2.68856
[3000]  test's rmse: 2.6562
[4000]  test's rmse: 2.642
[5000]  test's rmse: 2.63493
[6000]  test's rmse: 2.63045
[7000]  test's rmse: 2.6272
[8000]  test's rmse: 2.62522
[9000]  test's rmse: 2.62397
[10000] test's rmse: 2.62304
Early stopping, best iteration is:
[10005] test's rmse: 2.62304
```

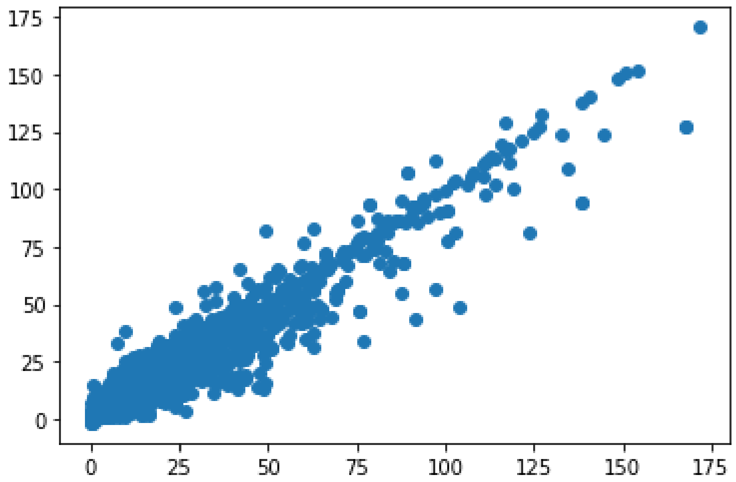
Out[197]:
```
LGBMRegressor(colsample_bytree=0.2, force_col_wise=True, learning_rate=0.01,
              metric='l2_root', n_estimators=20000, num_leaves=100,
              objective='regression', reg_alpha=3, reg_lambda=1, subsample=0.8)
```

In [195]:
```
y_test.mean() #5.18, average error on prediction with a 2.63 rmse gives ca. 50% error on predicton on average!
```

Out[195]:
```
5.187222050811799
```

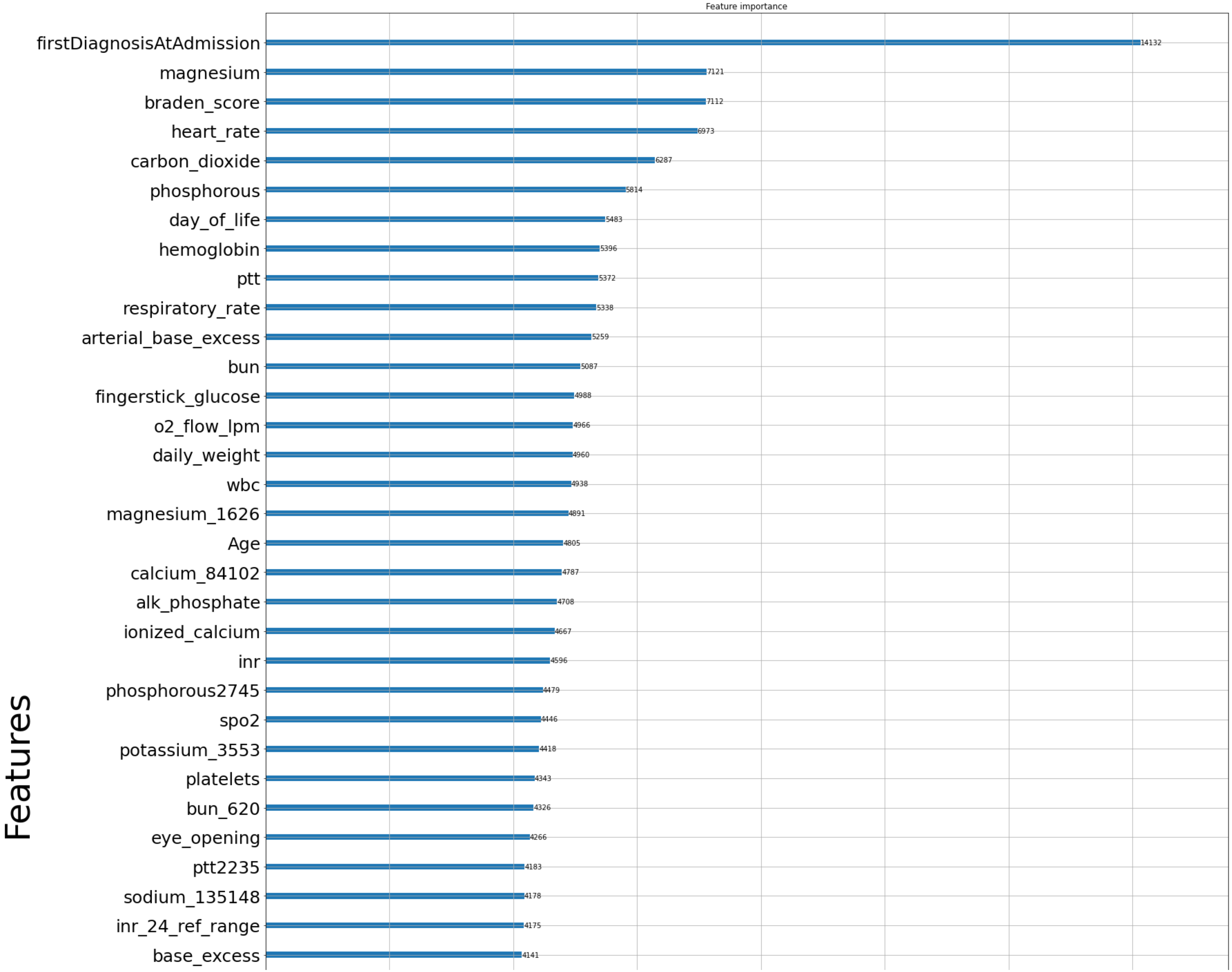
In [198]:
```
LoS_hat_2=clf_2.predict(X_test_2) #LoS is in days
plt.scatter(y_test, LoS_hat_2) # better it could be improved maybe with hyperopr hyperparameter optimization
```

Out[198]: <matplotlib.collections.PathCollection at 0x1aec74249c8>

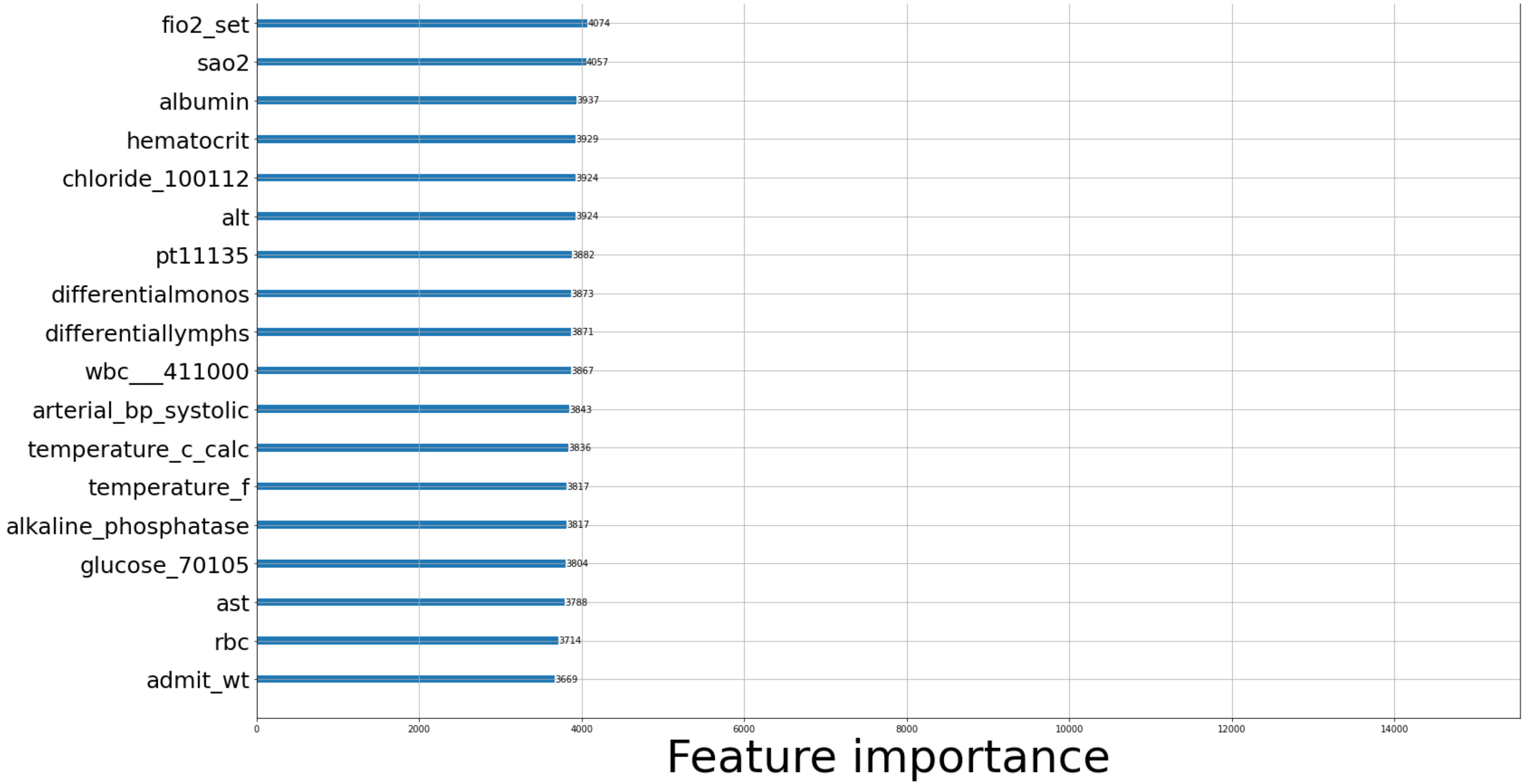


In [206]:

```
plt.rcParams['ytick.labelsize'] = 25
lgb.plot_importance(clf_2, max_num_features=50, figsize = (25,40))
plt.show()
# most relevant feature is diagnosis at admitance
#although diagnosis at admitance might contain some error,
#if some one is admitted to ICU they must be much strongely sure about the problem of the patient!!
```



Feature importance
Features
firstDiagnosisAtAdmission
magnesium
braden_score
heart_rate
carbon_dioxide
phosphorous
day_of_life
hemoglobin
ptt
respiratory_rate
arterial_base_excess
bun
fingerstick_glucose
o2_flow_lpm
daily_weight
wbc
magnesium_1626
Age
calcium_84102
alk_phosphate
ionized_calcium
inr
phosphorous2745
spo2
potassium_3553
platelets
bun_620
eye_opening
ptt2235
sodium_135148
inr_24_ref_range
base_excess
14132
7121
7112
6973
6287
5814
5483
5396
5372
5338
5259
5087
4988
4966
4960
4938
4891
4805
4787
4708
4667
4596
4479
4446
4418
4343
4326
4266
4183
4178
4175
4141


fio2_set
sao2
albumin
hematocrit
chloride_100112
alt
pt11135
differentialmonos
differentiallymphs
wbc___411000
arterial_bp_systolic
temperature_c_calc
temperature_f
alkaline_phosphatase
glucose_70105
ast
rbc
admit_wt
4074
4057
3937
3929
3924
3924
3882
3873
3871
3867
3843
3836
3817
3817
3804
3788
3714
3669
0
2000
4000
6000
8000
10000
12000
14000
Feature importance

In [ ]: