Examen midterm temas selectos de estadística II

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Contents

1 Análisis exploratorio de datos.

Al ser una base de datos sumamente extensa se tuvieron problemas de RAM por falta de memoria,a lo cual para poder hacer el tratamiento y análisis exploratorio de los datos, se hizo una división por "chunks" con 1M (millón) de registros en cada uno. En el caso del modelo supervisado, sólo se elijieron variables que nos ayudaran a predecir el volumen de rides por hora (pickup), las cuales son: Lectura de datos

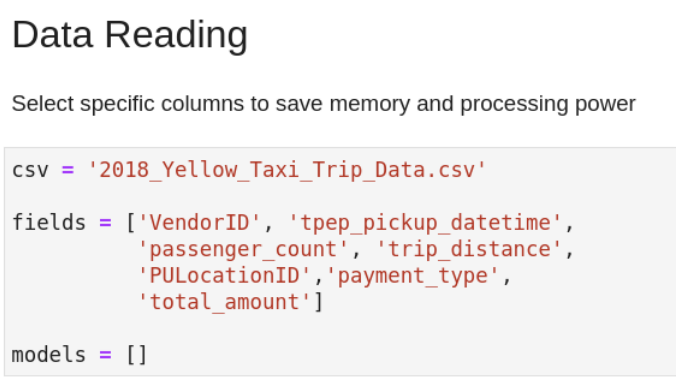


Figure 1: Lectura de datos

Una vez que ya tenemos nuestras variables, se leyó el archivo "csv", asignando los tipos de datos correspondientes para así poder evitar mayor uso de memoria RAM.

Como estamos usando el dataset por "chunk", elegimos utilizar el primero para así poder analizar y procesar la información. Revisamos si no tenemos datos faltantes: Datos faltantes

Figure 2: Check for null variables

No tenemos datos faltantes, por lo que se procede a limpiar información que no necesitamos. Al manejar datasets por particiones, debemos hacer todos los cálculos por funciones, por lo que nuestra primer función es: data_filter

[4]:
```python
def data_filter(df):
    ''' data_filter

    Filters data where:
        -Data is not from 2018
        -Total amount is less than zero
        -Passenger count is less than one
        -Trip distance is less or equal to zero

        -Drop passenger_count (we dont use it later in the model)

    Parameter
    ---------
    df: Dataframe chunk
    '''

    #Filters data not from 2018
    start_date = pd.to_datetime('2018-01-01 00:00:00')
    end_date = pd.to_datetime('2019-01-01 00:00:00')
    mask = (df['tpep_pickup_datetime'] >= start_date) & (df['tpep_pickup_datetime'] < end_date)
    df = df.loc[mask]

    #Filters data where total amount is less than zero
    df  = df[df["total_amount"] > 0.00]

    #Filters where passenger count is less than one
    df = df[df["passenger_count"] >= 1]

    #Filters where trip distance = 0
    df = df[df["trip_distance"] > 0]

    df.drop(['passenger_count'], axis=1, inplace = True)

    return df
```

Figure 3: Data filter function

Luego pasamos por otra función llamada "dates", la cual hace split de la columna "tpep_pickup_time" y la convierte en dos columnas; además, agrega "pickup_hour" para posteriormente hacer un catálogo de horas. Finalmente, corremos nuestro chunk de datos por una función llamada "hours_catalog" la cual nos regresa la columna "id_hour". hours catalog

Hours Catalog

[6]:
```python
def hours_catalog(df):
    '''hours_catalog

    Creates id_hour (int16) column based on pickup_hour sorted column

    Parameter
    --------
    df: Chunk of Dataframe that contains pickup_hour values:
        First two values: Month number
        Third and Fourth values: Day of the week {01: Monday .... 07:Sunday}
        Last two values: Hour

    '''
    catfh = df[['pickup_hour']].drop_duplicates().sort_values('pickup_hour',ascending=True).reset_index(drop=True)
    catfh["id_hour"] = (catfh.index+1)
    catfh["id_hour"] = catfh["id_hour"].astype('int16')

    df = df.merge(catfh, on='pickup_hour', how='inner')
    df.drop('pickup_hour', axis=1, inplace=True)

    return df
```

Figure 4: Función para catálogo de horas

2 Ingeniería de datos.

Una vez que ya pasamos por el proceso anterior y creamos nuestro catálogo de horas "id_hour", obtenemos el primer y último valor de esa columna para poder definir hora_inicial y hora_final. Luego definimos nuestra ventana de observación, la ventana de desempeño y nuestras anclas.

Además, definimos nuestra unidad muestral, nuestro step y nuestras variables continuas y discretas. variables

Data Engineering

[17]:
```
horai,horaf = df[['id_hour']].describe().T[['min','max']].values[0].tolist()
horai,horaf
```

[17]:
```
(1.0, 134.0)
```

[18]:
```
vobs = 24
vdes = 1
anclai = int(horai)+vobs-1
anclaf = int(horaf)-vdes
anclai,anclaf
```

[18]:
```
(24, 133)
```

[19]:
```
um = ['PULocationID', 'ancla']
ancla = 24
step = 4
varc = ['trip_distance', 'total_amount', 'n']
vard = ['hora']
```

Figure 5: Horas, Anclas y Steps

Posteriormente, pasamos a una función donde nos regrese un dataframe compuesto por todas variedades de nuestras variables, por ejemplo: trans

[20]:
```
%%time
X_test = pd.concat(map(lambda ancla:reduce(lambda x,y:pd.merge(x,y,on=um,how='outer'),
       map(lambda k:trans(df,ancla,k),range(step,vobs+step,step))),range(anclai,anclaf+1)),ignore_index=True)
```

```
CPU times: user 4min 58s, sys: 2.82 s, total: 5min 1s
Wall time: 5min 1s
```

[21]:
```
X_test.head()
```

[21]:

	PULocationID	v_hora_min_n_3_4	v_hora_min_n_total_hora_4	v_hora_min_total_amount_3_4	v_hora_min_total_amount_total_hora_4	v_ho
0	1	1.0	1.0	105.30	105.30	
1	4	1.0	1.0	5.80	5.80	
2	7	1.0	1.0	4.80	4.80	
3	10	1.0	1.0	35.38	35.38	
4	12	1.0	1.0	7.55	7.55	

Figure 6: Función trans

Después de tener X listo, creamos Y para luego proceder a la modelación: y

[22]:
```
y_test= pd.concat(map(lambda ancla: target(df,ancla,vdes),range(anclai,anclaf+1)),ignore_index=True)
y_test.head()
```

[22]:

	PULocationID	y	ancla
0	4	7	24
1	7	21	24
2	10	6	24
3	12	1	24
4	13	27	24

Figure 7: Creación de Y

3 Modelo supervisado.

3.1 Tabla analítica de datos (TAD).

Cuando ya tenemos Nuestras dos tablas X, Y, vamos a correr la función "TAD", la cual hace un merge entre estas dos tablas sobre la unidad muestral. tad

Creación de TAD (Tabla analítica de datos) $\vec{y} = f(\mathcal{X})$

```
tad_test = TAD(X_test,y_test,um)
tad_test.head()
```

	PULocationID	v_hora_min_n_3_4	v_hora_min_n_total_hora_4	v_hora_min_total_amount_3_4
0	4	1.0	1.0	5.80
1	7	1.0	1.0	4.80
2	10	1.0	1.0	35.38
3	12	1.0	1.0	7.55
4	13	1.0	1.0	0.31

Figure 8: TAD

3.2 Valores ausentes e imputación

Luego de haber conseguido la TAD, nos aseguramos si hay valores ausentes en ella. Si hay valores ausentes en TAD, pasamos por una función "impute" la cual nos va a regresar dos variables: imputar

Impute

[10]:
```python
def impute(tad, varc):
    '''impute

    Returns
    X: Based on TAD column with only columns from varc list
    Xi: Imputed df based on X with median strategy

    Parameters
    ..........
    tad: TAD table
    varc: list of continued variables

    '''

    X = tad[varc].copy()
    im = SimpleImputer(strategy='median')
    im.fit(X)
    Xtrans = im.transform(X)

    Xi = pd.DataFrame(Xtrans, columns=varc)

    #Kolmogorov-Smirnov (Two distributions are statistically equal)
    ks = pd.DataFrame(map(lambda v: (v,ks_2samp(tad[v].dropna(),Xi[v]).statistic),varc),columns=['variable','ks'])
    print(ks.loc[ks['ks']>.1])

    return X, Xi
```

Figure 9: Imputación

3.3 Valores extremos.

Para poder cuantificar todos nuestros valores extremos, pasamos nuestro dataset, unidad muestra y TAD a nuestra función "extreme" la cual nos imprimirá la cantidad de valores extremos en nuestro chunk de datos. extremos

Valores Extremos

[27]:
```
extreme(X_test, um, tad_test)
```

```
count    9585.000000
mean        0.509442
std         0.499937
min         0.000000
25%         0.000000
50%         1.000000
75%         1.000000
max         1.000000
Name: extremo, dtype: float64
```

Figure 10: Valores extremos

Como podemos dar cuenta, la cantidad de valores extremos representa un 0.95% de nuestro chunk.

3.4 Modelación.

Cuando hayamos conseguido nuestra tabla Xi (imputada), podemos seguir con nuestro modelo. Para ello pasamos a nuestra función "regression" la cual necesita los parámetros (tad, tgt, Xi).

En esta función vamos a hacer un split de nuestro chunk entre "train" y "test" para luego buscar los mejores hiperparámetros a través de "GridSearchCV" y para ello ya podemos hacer fit de nuestros datos.

Para poder verificar nuestro modelo, se imprimen los mean absolute error, primero con los valores de entrenamiento y después los valores para testing: mean errors

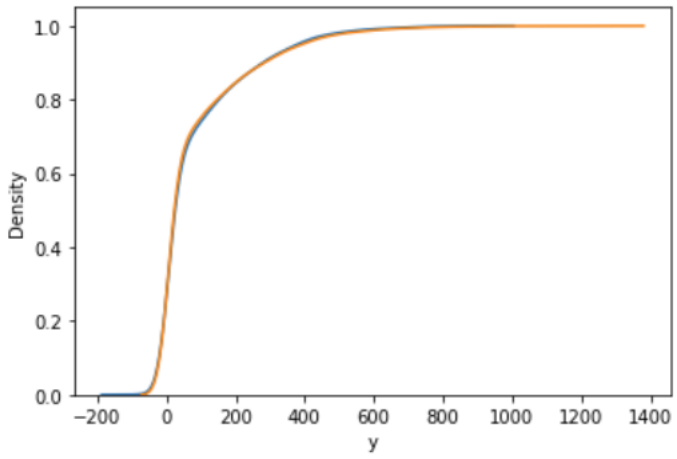
```
[34]: print(mean_absolute_error(y_true=yt_test,y_pred=modelo_test.predict(Xt_test)))
      print(mean_absolute_error(y_true=yv_test,y_pred=modelo_test.predict(Xv_test)))

      22.515774748259656
      22.701732484535974
```

Figure 11: Mean absolute error

Otra forma de ver la funcionalidad de nuestro modelo, es con las siguientes gráficas. La primer gráfica es con datos de training y la segunda con datos de testing: graficas

[35]:
```
sns.distplot(modelo_test.predict(Xt_test),hist=False,kde_kws={'cumulative':True})
sns.distplot(yt_test,hist=False,kde_kws={'cumulative':True})
```

[35]:
```
<AxesSubplot:xlabel='y', ylabel='Density'>
```



[36]:
```
sns.distplot(modelo_test.predict(Xv_test),hist=False,kde_kws={'cumulative':True})
sns.distplot(yv_test,hist=False,kde_kws={'cumulative':True})
```

[36]:
```
<AxesSubplot:xlabel='y', ylabel='Density'>
```

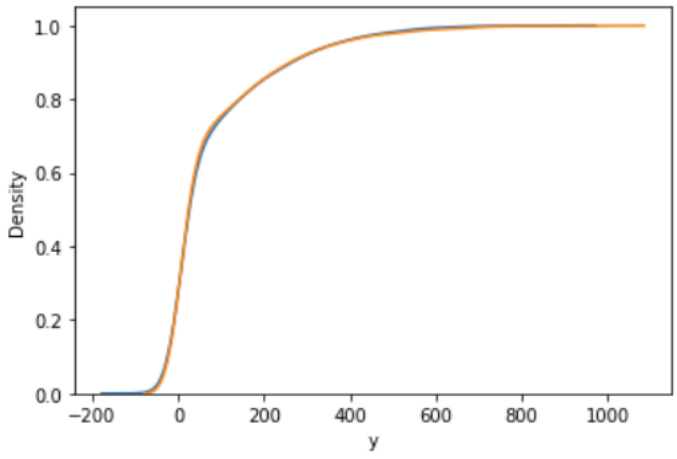


Figure 12: Gráficas del modelo

3.5 Corriendo los chunks

Al inicio de esta sección, se comentó que se usaron funciones al correr el proceso y, al momento de decirle a pandas que usaremos chunks, este nos regresa un iterador, el cual podemos usar en un for y así correr todos los modelos y haciendo append a una lista.

3.5.1 Predecir con todos los modelos

En estas ocaciones de modelado, lo ideal es usar la media de las predicciones de todos los modelos y así tener un resultado óptimo.

3.6 Persistencia

Ya que este es un modelado bastante pesado computacionalmente, lo ideal es que guardemos todos los modelos de nuestros chunks, para eso usaremos la librería "pickle" de la siguiente forma: pickle

[40]:
```
import pickle
```

[45]:
```
with open("models_other.pkl", "wb") as f:
    for model in models:
         pickle.dump(model, f)
```

Si queremos abrir los modelos de nuevo para evitar entrenamiento

[42]:
```
new_models = []
with open("models.pckl", "rb") as f:
    while True:
        try:
            new_models.append(pickle.load(f))
        except EOFError:
            break
```

[44]:
```
len(new_models)
```

[44]: 112

Figure 13: Persistencia modelo supervisado

Lo que estamos haciendo aquí, es guardar todos los modelos de nuestra lista en un mismo archivo. Si luego queremos leer esos modelos, simplemente los guardamos en una lista.

4 Modelo no supervisado.

4.1 Lectura de datos y limpieza.

En el caso del modelo no supervisado usamos la librería "Dask" de computación paralela al leer nuestro dataset y limpiarlo más eficiente. Similar a nuestro modelo supervisado, pasamos las variable que vayamos a utilizar para el clustering: lectura

```
csv = '2018_Yellow_Taxi_Trip_Data.csv'

fields = ['passenger_count', 'trip_distance', 'tip_amount',
          'total_amount', 'PULocationID', 'DOLocationID']
```

```
temp =dd.read_csv(csv,
                  usecols=fields,
                  dtype={'passenger_count':'int8', 'trip_distance':'float32',
                         'total_amount':'float32', 'PULocationID': 'int16',
                         'DOLocationID':'int16', 'tip_amount': 'float16'})
```

Figure 14: Lectura de datos modelo no supervisado

Una vez leído nuestro "dask dataframe" hacemos una descripción para datos ilógicos y procedemos a limpiarlos. filtro

```
[4]: temp = temp[temp['passenger_count'] > 0]
     temp = temp[temp['passenger_count'] < 7]
     temp = temp[temp['trip_distance'] > 0]
     temp = temp[temp['total_amount'] > 0]
```

Figure 15: Limpieza datos modelo no supervisado

4.2 Visualización.

Después de haber filtrado los datos, sacamos una muestra de nuestra información y lo convertimos a un dataframe de pandas, luego seleccionamos nuestras variables continuas y procedemos con el procesamiento.

4.2.1 PCA

Para las variables que seleccionamos, y al hacer un "StandardScaler", obtenemos una explicación de la varianza del 74% en dos dimensiones.
pca

PCA

```
[10]: sc = StandardScaler()
      sc.fit(X)
      Xs = pd.DataFrame(sc.transform(X),columns=varc)
      pca = PCA(n_components=2)
      pca.fit(Xs)
      pca.explained_variance_ratio_.cumsum()

[10]: array([0.5179963 , 0.74349976], dtype=float32)

[11]: Xp = pd.DataFrame(pca.transform(Xs),columns=['d1','d2'])

[12]: sns.lmplot(data=Xp,x='d1',y='d2',fit_reg=False)

[12]: <seaborn.axisgrid.FacetGrid at 0x7f574c407550>
```

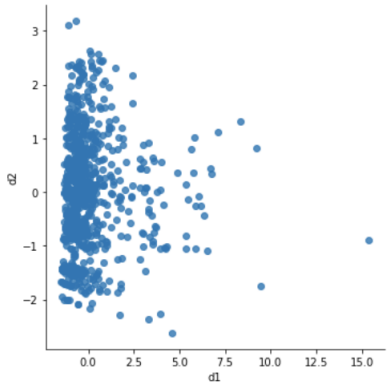


Figure 16: PCA

4.2.2 MDS

mds

MDS

```
[13]: mds = MDS(n_components=2,n_jobs=-1)
      Xm = pd.DataFrame(mds.fit_transform(X),columns=['d1','d2'])
      sns.lmplot(data=Xm,x='d1',y='d2',fit_reg=False)
```

```
[13]: <seaborn.axisgrid.FacetGrid at 0x7f574c3175f8>
```

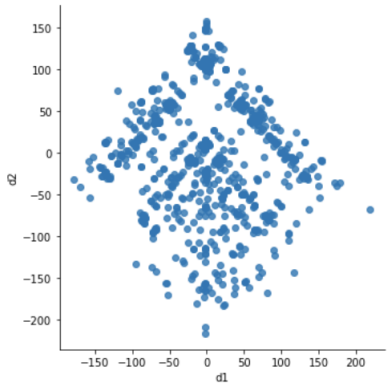


Figure 17: MDS

En MDS no podemos ver algún cluster con claridad

4.2.3 T-SNE

tsne

T-SNE

```
[14]: tsne = TSNE(n_components=2,n_jobs=-1)
      Xt = pd.DataFrame(tsne.fit_transform(X),columns=['d1','d2'])
      sns.lmplot(data=Xt,x='d1',y='d2',fit_reg=False)
```

```
[14]: <seaborn.axisgrid.FacetGrid at 0x7f574c2dfa58>
```

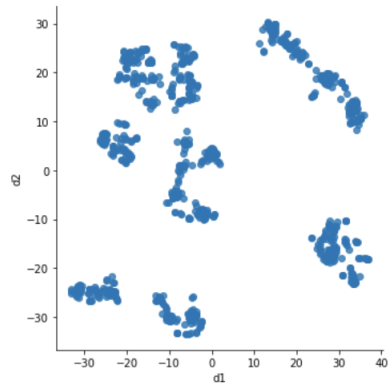


Figure 18: T-SNE

En T-SNE podemos ver un poco mejor algunos clusters

4.3 Número de clusters

Luego de haber visto la reducción de dimensiones y el análisis de correlaciones, pasamos a ver una gráfica de "codo" para determinar cuántos clusters haremos. codo

```
[18]: [<matplotlib.lines.Line2D at 0x7f5768fc6240>]
```

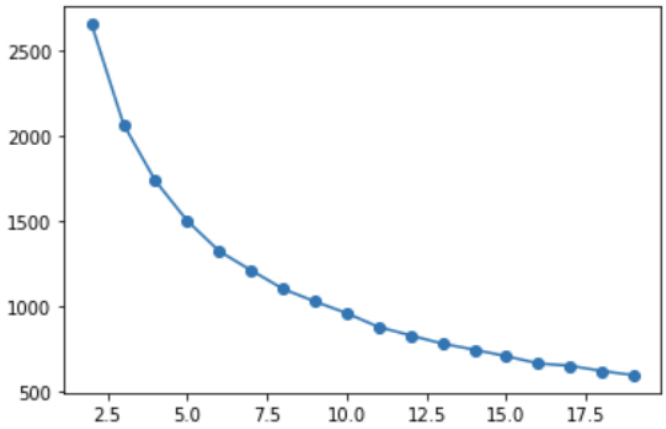


Figure 19: Gráfica de "codo"

En este caso vamos a tomar de referencia 7 clusters

4.3.1 Aglomerativo

Los porcentajes en este algoritmo son: aglomerativo

```
0    0.052761
1    0.360736
2    0.020859
3    0.134969
4    0.139877
5    0.160736
6    0.130061
Name: agg, dtype: float64
```

[21]: <AxesSubplot:ylabel='agg'>

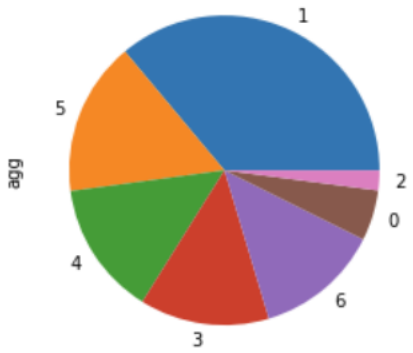


Figure 20: Aglomerativo

4.3.2 K-Means

Porcenyajes en K-Mean: k-means

```
0    0.166871
1    0.195092
2    0.285890
3    0.022086
4    0.072393
5    0.236810
6    0.020859
Name: kme, dtype: float64
```

[22]: <AxesSubplot:ylabel='kme'>

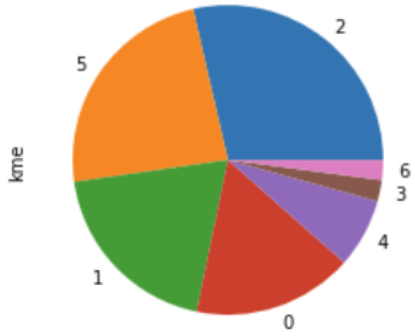


Figure 21: K-Means

4.3.3 Gaussian Mixture

Como podemos ver, la mezcla Gaussiana nos da una mejor distribución en el cluster gauss

```
0    0.159509
1    0.050307
2    0.269939
3    0.132515
4    0.169325
5    0.107975
6    0.110429
Name: gau, dtype: float64
```

[23]: <AxesSubplot:ylabel='gau'>

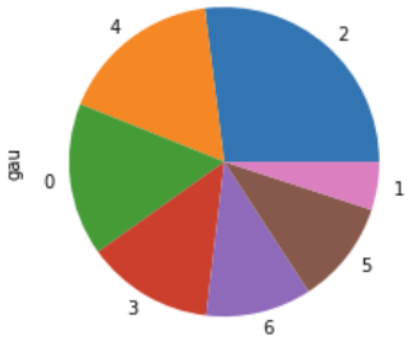


Figure 22: Gaussiana

4.3.4 Visualización 2D T-SNE y Gauss

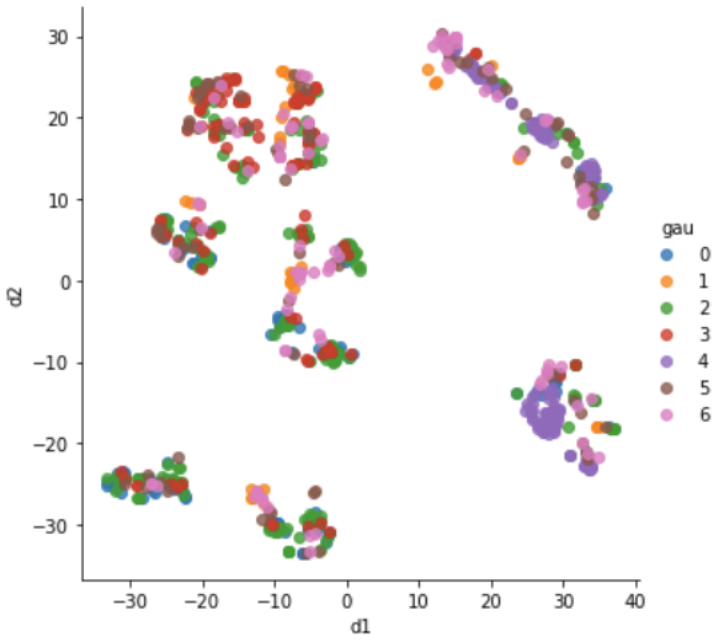


Figure 23: T-SNE con Gauss

En la figura anterior podemos observar que, aunque los clusters están mezclados, algunos colores dominan, en el lado derecho se puede aprecuar un dominio del cluster 4 mientras que en la esquina inferior izquierda hay más cluster 2

4.4 Perfilamiento.

Para poder verificar qué variables nos son más útiles para hacer clustering, debemos hacer un perfilamiento considerando el p-value. Una forma alternativa es usando el método "SelectKBest", el cual nos dice que todas nuestras variables son significativas.

4.5 Ejemplos.

Para observar nuestro clustering, podemos hacer lo siguiente: ejemplos

[64]:
```
k = 5
cl = 2
for id in df.loc[df['gau']==cl].sample(k).DOLocationID:
    print(id)
```

```
140
142
246
224
238
```

[69]:
```
i = 5
cluster = 4
for id in df.loc[df['gau']==cluster].sample(i).trip_distance:
    print(id)
```

```
0.699999988079071
1.2999999523162842
0.4699999988079071
0.6000000238418579
0.49000000953674316
```

Figure 24: Ejemplos modelo no supervisado

5 Estrategia de aplicación de los modelos.

Algunas propuestas para hacer uso de estos modelos son:

5.1 Modelo supervisado:

1. Predicción de demanda general y/o por zona: Al tener como base la locación donde se tomó el taxi, podemos generalizar para todo Nueva York o para una zona en específico. Además de mejorar costos al reducir el número de taxis dependiendo la hora del día.

2. Predicción taxis disponible: Con una pequeña modificación, podemos predecir cuántos taxis se liberan cada hora para así poder mover a los taxis a las zonas con mayor tráfico de clientes.

5.2 Modelo no supervisado:

1. Clusterización de zonas: Podemos hacer clusters de qué zonas son las que toman viajes más largos/cortos, las zonas con ticket promedio más alto. Y haciendo una combinación con el modelo supervisado, optimizar recursos para obtener mayores ingresos.

2. Clusters con mayor número de pasajeros: Con una modficación podríamos arreglar este algoritmo para mover carros más grandes a zonas donde los viajes tienen más ocupantes.

5.3 Nota.

En ambos modelos, las propuestas se pueden implementar de diferentes formas, ya sea que se predija con un servicio cloud a una aplicación web ó podemos exportar los modelos y hacer un dashboard para que equipos de business development tomen las mejores decisiones.

6 Conclusiones.

Al hacer este tipo de proyectos, se debe tener muy en cuenta toda la ingeniería de datos; ya que, si no la hacemos de la forma correcta nuestros modelos serán erroneos y no generalizarán. Por otro lado es interesante ver cómo se desarrolla el backend de muchas de las aplicaciones que usamos en la vida cotidiana en las cuales existen algoritmos de recomendación, mejor ruta, etc.

Una alternativa para el modelo supervisado sería probar con el algoritmo de redes neuronales y ver la diferencia de eficiencia comparado con regresión lineal. Además indagar en otras formas de procesamiento de la información; ya que, con chunks es bastante tardado debido a que pandas sólo utiliza un núcleo del procesador, tres posibles soluciones son: pasar la información a una base de datos SQL (aprovechando nuestras funciones), sacando una muestra para así ahorrarnos poder de cómputo ó finalmente usando la librería "Dask" de cómputo paralelo para poder procesar la información.

7 Anexos.

Los anexo con los códigos en Jupyter empiezan en la siguiente página.

Linear Model

Libraries

In [1]:
```
import pandas as pd
import numpy as np
import os
from functools import reduce
from datetime import date,datetime

from scipy.stats import ks_2samp

from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LinearRegression

from sklearn.metrics import mean_absolute_error
from sklearn.metrics import roc_auc_score,accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV,RandomizedSearchCV

import matplotlib.pyplot as plt
import seaborn as sns
import pygal
from scikitplot.metrics import plot_roc_curve

import warnings
warnings.filterwarnings('ignore')

%matplotlib inline
pd.set_option('display.max_columns',500)
```

Data Reading

Select specific columns to save memory and processing power

In [2]:
```
csv = '2018_Yellow_Taxi_Trip_Data.csv'

fields = ['VendorID', 'tpep_pickup_datetime',
          'passenger_count', 'trip_distance',
          'PULocationID','payment_type',
          'total_amount']

models = []
```

In [3]:
```
iterator = pd.read_csv(csv, usecols=fields,
                       dtype={'VendorID': 'int8','passenger_count':'int8',
                              'trip_distance':'float32', 'PULocationID':'int16',
                              'payment_type':'int8', 'total_amount':'float32'},
                       parse_dates=["tpep_pickup_datetime"],
                       chunksize=1000000)
```

Functions

Data Filter

In [4]:
```
def data_filter(df):
    ''' data_filter

    Filters data where:
        -Data is not from 2018
        -Total amount is less than zero
        -Passenger count is less than one
        -Trip distance is less or equal to zero

        -Drop passenger_count (we dont use it later in the model)

    Parameter
    ---------
    df: Dataframe chunk
    '''

    #Filters data not from 2018
    start_date = pd.to_datetime('2018-01-01 00:00:00')
    end_date = pd.to_datetime('2019-01-01 00:00:00')
    mask = (df['tpep_pickup_datetime'] >= start_date) & (df['tpep_pickup_datetim
    df = df.loc[mask]

    #Filters data where total amount is less than zero
    df  = df[df["total_amount"] > 0.00]

    #Filters where passenger count is less than one
    df = df[df["passenger_count"] >= 1]

    #Filters where trip distance = 0
    df = df[df["trip_distance"] > 0]

    df.drop(['passenger_count'], axis=1, inplace = True)

    return df
```

In [5]:
```
def dates(df):
    '''dates

    Splits Datetime into two new columns:
        -pickup_date
        -pickup_hour

    Adds column:
        -pickup_hour where: First two digits represent month,
                            Middle two represent day of the week
                            Last two represent the pickup hour

    Drops the original datetime column

    Parameter
    ---------
    df: Dataframe chunk
    '''
    df['pickup_date'] = df['tpep_pickup_datetime'].dt.date

    df['pickup_time'] = df['tpep_pickup_datetime'].dt.time
    df['pickup_time'] = df['pickup_time'].astype(str)
```

```
    ##df['month'] = pd.to_datetime(df['tpep_pickup_datetime'].dt.month)
    df['month'] = df['tpep_pickup_datetime'].dt.strftime('%m')

    #Day of week {01: Monday .... 07:Sunday}
    df['pickup_day_of_week'] = df['tpep_pickup_datetime'].dt.dayofweek +1
    df['pickup_day_of_week'] = '0' + df['pickup_day_of_week'].astype(str)

    df['hour'] = df['tpep_pickup_datetime'].dt.strftime('%H')

    df["pickup_hour"] = df['month'] + df['pickup_day_of_week'] + df['hour']

    df.drop(["tpep_pickup_datetime",
             "month",
             "pickup_day_of_week",
             "hour"], axis=1, inplace=True)

    return df
```

Hours Catalog

In [6]:

```
def hours_catalog(df):
    '''hours_catalog

    Creates id_hour (int16) column based on pickup_hour sorted column

    Parameter
    --------
    df: Chunk of Dataframe that contains pickup_hour values:
        First two values: Month number
        Third and Fourth values: Day of the week {01: Monday .... 07:Sunday}
        Last two values: Hour

    '''
    catfh = df[['pickup_hour']].drop_duplicates().sort_values('pickup_hour',asce
    catfh["id_hour"] = (catfh.index+1)
    catfh["id_hour"] = catfh["id_hour"].astype('int16')

    df = df.merge(catfh, on='pickup_hour', how='inner')
    df.drop('pickup_hour', axis=1, inplace=True)

    return df
```

Data Engineering

In [7]:

```
def trans(df,ancla,k):
    '''trans

    Parameters
    -----------
    df: Chunk of Dataframe
    ancla: current ancla to run
    k: current step
    '''

    aux = df.loc[(df['id_hour']>=(ancla-k+1))&(df['id_hour']<=ancla)].reset_inde
    aux = aux[['id_hour', 'trip_distance', 'total_amount', 'pickup_time','PULoca
    aux['hora'] = aux['pickup_time'].map(lambda x:int(x.split(':')[0])//6).astyp
    aux.drop('pickup_time',axis=1,inplace=True)
    aux['n'] = 1
```

```
    t = aux.copy()

    for v in vard:
        t[v] = 'total_%s'%v
    aux = pd.concat([aux,t],ignore_index=True)

    def piv(aux,v,ancla):
        aux = aux.pivot_table(index='PULocationID',
                              columns=v,
                              values=varc,
                              aggfunc=['min','max','mean','sum','std'])

        aux.columns = ["v_%s_"%v+"_".join(x)+"_%d"%k for x in aux.columns]
        return aux.reset_index().assign(ancla=ancla)

    aux = reduce(lambda x,y:pd.merge(x,y,on=um,how='outer'),map(lambda v:piv(aux
    return aux
```

TAD & Target

In [8]:
```
def TAD(X, y, um):

    tad = X.merge(y,on=um,how='inner')

    return tad
```

In [9]:
```
def target(df, ancla, vdes):
    aux = df.loc[(df['id_hour']>ancla)&(df['id_hour']<=(ancla+vdes))].reset_inde
    aux = aux.groupby(um[0]).sum()
    return aux.assign(ancla=ancla).reset_index()
```

Impute

In [10]:
```
def impute(tad, varc):
    '''impute

    Returns
    X: Based on TAD column with only columns from varc list
    Xi: Imputed df based on X with median strategy

    Parameters
    ..........
    tad: TAD table
    varc: list of continued variables

    '''

    X = tad[varc].copy()
    im = SimpleImputer(strategy='median')
    im.fit(X)
    Xtrans = im.transform(X)

    Xi = pd.DataFrame(Xtrans, columns=varc)

    #Kolmogorov-Smirnov (Two distributions are statistically equal)
    ks = pd.DataFrame(map(lambda v: (v,ks_2samp(tad[v].dropna(),Xi[v]).statistic
    print(ks.loc[ks['ks']>.1])
```

```
    return X, Xi
```

Extreme Values

In [11]:
```
def extremo(df,v,ci,cs):
    aux = df[um+[v]].copy()
    aux['ol_%s'%v] = ((aux[v]<ci)|(aux[v]>cs)).astype(int)
    return aux.drop(v,axis=1)


def extreme(X, um, tad):

    cotas = X.describe(percentiles=[0.01,0.99]).T[['1%', '99%']].reset_index().v
    ext = reduce(lambda x,y:pd.merge(x,y,on=um,how='outer'),map(lambda z:extremo
    varol = [v for v in ext if v[:2]=='ol']
    ext['extremo'] = ext[varol].max(axis=1)
    print(ext['extremo'].describe())
```

Modelling (Find parameters $\vec{\theta}$ of model f for $\vec{y} = f(\mathcal{X}) \rightarrow y = \theta_0 + \vec{\theta} \cdot \vec{x}$

In [12]:
```
def regression(tad, tgt, Xi):
    '''regression

    Creates a linear model for the df passed.
    Appends the model to the models list so we can dump it with pickle

    Parameters
    ----------
    tad: TAD table for the dataframe chunk
    tgt: target column
    Xi: table with imputed values

    '''


    y = tad[tgt].copy()
    Xt,Xv,yt,yv = train_test_split(Xi,y,train_size=0.7)
    modelo = LinearRegression()
    hiperparametros=dict(fit_intercept=[True,False],normalize=[True,False])

    grid = GridSearchCV(param_grid=hiperparametros,
                        estimator=modelo,
                        cv=10,
                        scoring='neg_mean_absolute_error',
                        n_jobs=-1,
                        verbose=True)
    grid.fit(Xt,yt)

    modelo = grid.best_estimator_
    modelo.fit(Xt,yt)
    modelo.intercept_

    print(mean_absolute_error(y_true=yt,y_pred=modelo.predict(Xt)))
    print(mean_absolute_error(y_true=yv,y_pred=modelo.predict(Xv)))

    Xv['y^'] = modelo.predict(Xv)
```

```
    Xv['y'] = yv
    modelo.coef_

    models.append(modelo)
```

First Chunk

Get the first chunk of data to test our functions

In [13]:
```
%%time
df = iterator.get_chunk()
```

```
CPU times: user 1min 18s, sys: 26.2 ms, total: 1min 18s
Wall time: 1min 19s
```

In [14]:
```
df.isnull().sum()
```

Out[14]:
```
VendorID               0
tpep_pickup_datetime   0
passenger_count        0
trip_distance          0
PULocationID           0
payment_type           0
total_amount           0
dtype: int64
```

No missing data, no need to worry. We next filter the data for 2018.

In [15]:
```
%%time
df = data_filter(df)
df = dates(df)
```

```
CPU times: user 11.6 s, sys: 318 ms, total: 11.9 s
Wall time: 11.9 s
```

Hours Catalog

In [16]:
```
df = hours_catalog(df)
df.head()
```

Out[16]:

	VendorID	trip_distance	PULocationID	payment_type	total_amount	pickup_date	pickup_time	id_l
0	2	8.00	230	2	26.80	2018-09-22	23:46:37	
1	2	1.70	141	1	11.76	2018-09-22	23:00:43	
2	2	3.84	163	2	15.30	2018-09-22	23:10:32	
3	2	1.80	166	2	9.80	2018-09-22	23:27:25	
4	2	2.43	229	1	13.30	2018-09-22	23:50:39	

Data Engineering

In [17]:
```
horai,horaf = df[['id_hour']].describe().T[['min','max']].values[0].tolist()
horai,horaf
```

Out[17]:
```
(1.0, 134.0)
```

In [18]:
```
vobs = 24
vdes = 1
anclai = int(horai)+vobs-1
anclaf = int(horaf)-vdes
anclai,anclaf
```

Out[18]: (24, 133)

In [19]:
```
um = ['PULocationID', 'ancla']
ancla = 24
step = 4
varc = ['trip_distance', 'total_amount', 'n']
vard = ['hora']
```

In [20]:
```
%%time
X_test = pd.concat(map(lambda ancla:reduce(lambda x,y:pd.merge(x,y,on=um,how='ou
       map(lambda k:trans(df,ancla,k),range(step,vobs+step,step))),range(anclai,
```

```
CPU times: user 4min 58s, sys: 2.82 s, total: 5min 1s
Wall time: 5min 1s
```

In [21]:
```
X_test.head()
```

Out[21]:

	PULocationID	v_hora_min_n_3_4	v_hora_min_n_total_hora_4	v_hora_min_total_amount_3_4	v_hora
0	1	1.0	1.0	105.30	
1	4	1.0	1.0	5.80	
2	7	1.0	1.0	4.80	
3	10	1.0	1.0	35.38	
4	12	1.0	1.0	7.55	

In [22]:
```
y_test= pd.concat(map(lambda ancla: target(df,ancla,vdes),range(anclai,anclaf+1)
y_test.head()
```

Out[22]:

	PULocationID	y	ancla
0	4	7	24
1	7	21	24
2	10	6	24
3	12	1	24
4	13	27	24

TAD (Tabla analítica de datos) $\vec{y} = f(\mathcal{X})$

In [23]:
```
tad_test = TAD(X_test,y_test,um)
tad_test.head()
```

Out[23]:

	PULocationID	v_hora_min_n_3_4	v_hora_min_n_total_hora_4	v_hora_min_total_amount_3_4	v_hora
0	4	1.0	1.0	5.80	
1	7	1.0	1.0	4.80	

	PULocationID	v_hora_min_n_3_4	v_hora_min_n_total_hora_4	v_hora_min_total_amount_3_4	v_hora
2	10	1.0	1.0	35.38	
3	12	1.0	1.0	7.55	
4	13	1.0	1.0	0.31	

Exploratory Analysis

Variable Selection

In [24]:
```
varc_test = [v for v in tad_test.columns if v[:2]=="v_"]
tgt_test = 'y'
```

Missing Values Counting

In [46]:
```
miss_test = 1-tad_test[varc_test].describe().T[['count']]/len(tad_test)
miss_test.describe()
```

Out[46]:

	count
count	450.000000
mean	0.293301
std	0.224234
min	0.000000
25%	0.113302
50%	0.231716
75%	0.467293
max	0.736255

Impute

In [26]:
```
X_test, Xi_test = impute(tad_test, varc_test)
```

```
                         variable        ks
2     v_hora_min_total_amount_3_4  0.329459
4    v_hora_min_trip_distance_3_4  0.345802
8     v_hora_max_total_amount_3_4  0.345092
10   v_hora_max_trip_distance_3_4  0.346276
14   v_hora_mean_total_amount_3_4  0.346986
..                            ...       ...
444              v_hora_sum_n_2_4  0.328851
445   v_hora_sum_total_amount_2_4  0.328851
446  v_hora_sum_trip_distance_2_4  0.328851
448   v_hora_std_total_amount_2_4  0.344966
449  v_hora_std_trip_distance_2_4  0.344966

[181 rows x 2 columns]
```

Valores Extremos

In [27]:
```
extreme(X_test, um, tad_test)
```

```
count    9585.000000
mean        0.509442
std         0.499937
min         0.000000
25%         0.000000
50%         1.000000
75%         1.000000
max         1.000000
Name: extremo, dtype: float64
```

Modelación (encontrar los parámetros $\vec{\theta}$ del modelo f para $\vec{y} = f(\mathcal{X}) \rightarrow y = \theta_0 + \vec{\theta} \cdot \vec{x}$

In [28]:
```
tad_test.head()
```

Out[28]:

	PULocationID	v_hora_min_n_3_4	v_hora_min_n_total_hora_4	v_hora_min_total_amount_3_4	v_hora
0	4	1.0	1.0	5.80	
1	7	1.0	1.0	4.80	
2	10	1.0	1.0	35.38	
3	12	1.0	1.0	7.55	
4	13	1.0	1.0	0.31	

In [29]:
```
y_test = tad_test['y'].copy()
Xt_test,Xv_test,yt_test,yv_test = train_test_split(Xi_test,y_test,train_size=0.7
modelo_test = LinearRegression()
hiperparametros=dict(fit_intercept=[True,False],normalize=[True,False])

grid_test = GridSearchCV(param_grid=hiperparametros,
                estimator=modelo_test,
                cv=10,
                scoring='neg_mean_absolute_error',
                n_jobs=-1,
                verbose=True)
```

In [30]:
```
grid_test.fit(Xt_test,yt_test)
```

```
Fitting 10 folds for each of 4 candidates, totalling 40 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:    7.7s finished
```

Out[30]:
```
GridSearchCV(cv=10, estimator=LinearRegression(), n_jobs=-1,
             param_grid={'fit_intercept': [True, False],
                         'normalize': [True, False]},
             scoring='neg_mean_absolute_error', verbose=True)
```

In [31]:
```
modelo_test = grid_test.best_estimator_
```

In [32]:
```
modelo_test.fit(Xt_test,yt_test)
```

Out[32]:
```
LinearRegression(fit_intercept=False, normalize=True)
```

In [33]:
```
modelo_test.intercept_
```

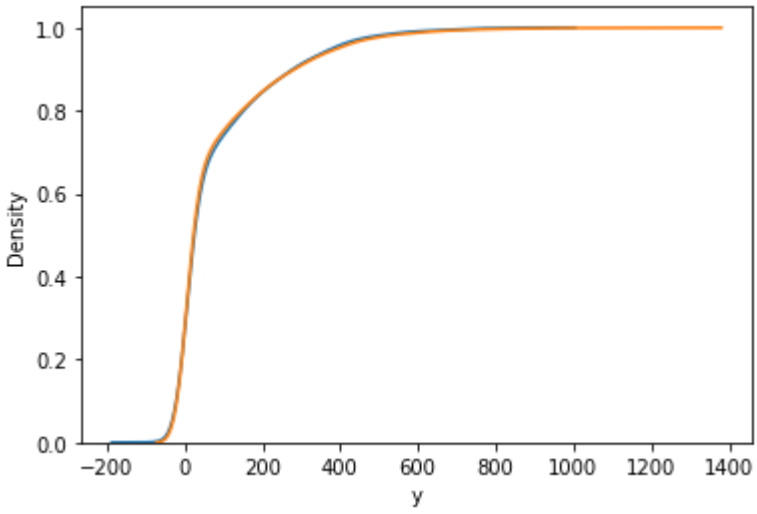
Out[33]:
```
0.0
```

In [34]:
```
print(mean_absolute_error(y_true=yt_test,y_pred=modelo_test.predict(Xt_test)))
print(mean_absolute_error(y_true=yv_test,y_pred=modelo_test.predict(Xv_test)))
```

```
22.515774748259656
22.701732484535974
```

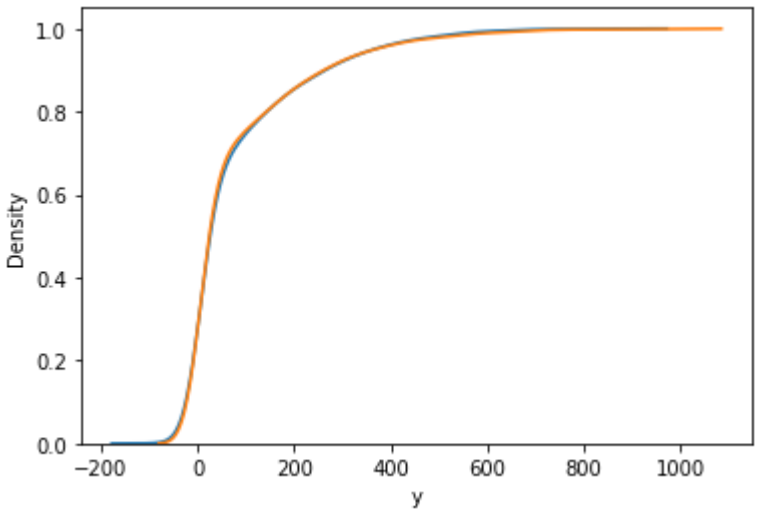
In [35]:
```
sns.distplot(modelo_test.predict(Xt_test),hist=False,kde_kws={'cumulative':True})
sns.distplot(yt_test,hist=False,kde_kws={'cumulative':True})
```

Out[35]:
```
<AxesSubplot:xlabel='y', ylabel='Density'>
```



In [36]:
```
sns.distplot(modelo_test.predict(Xv_test),hist=False,kde_kws={'cumulative':True})
sns.distplot(yv_test,hist=False,kde_kws={'cumulative':True})
```

Out[36]:
```
<AxesSubplot:xlabel='y', ylabel='Density'>
```



In [37]:
```
Xv_test['y^'] = modelo_test.predict(Xv_test)
Xv_test['y'] = yv_test
```

In [38]:
```
modelo_test.coef_
```

Out[38]:
```
array([-1.48760393e-01, -1.48760393e-01,  1.33688497e-01, -8.21227846e-01,
       -1.80719876e-01,  1.03225620e+00, -1.48760393e-01, -1.48760393e-01,
```

```
 3.47944646e-01, -1.04221773e-03, -1.30113183e+00, -4.62142203e-03,
-1.48760393e-01, -1.48760393e-01,  2.49133424e-02,  7.01695131e-01,
-7.00091044e-01, -8.87602136e-02, -1.24168639e+00,  1.17520706e+00,
 1.25832842e-02,  2.84669706e-02,  3.69635076e-01, -5.15159571e-01,
 1.14446785e-11, -1.80533366e-12, -7.77923529e-01, -7.69044832e-01,
 2.89467352e+00,  1.30259978e-01, -1.48760393e-01, -1.48760393e-01,
-1.48760393e-01,  1.07424143e+00,  5.39737947e-01, -3.65926858e-01,
-5.71023681e-01, -2.96726946e+00,  1.29557904e+00, -1.48760393e-01,
-1.48760393e-01, -1.48760393e-01, -4.76540925e-01, -1.75090748e-01,
 2.93042754e-01,  1.09945962e+00,  1.09507451e+00, -9.74702102e-01,
-1.48760393e-01, -1.48760393e-01, -1.48760393e-01, -7.57862669e-01,
-7.88799788e-01, -1.52582439e-02, -1.28742316e+00,  2.97879228e+00,
 2.75856969e-01, -1.70366949e+00, -1.33331046e+00,  1.45210675e+00,
 7.35876946e-02,  3.09158991e-02, -5.04361851e-02,  1.00563833e-01,
 2.19445916e-01, -1.41264099e-01, -1.61537450e-14, -1.33920652e-13,
 9.45493683e-14,  1.89428444e+00,  8.11460776e-01, -5.57794434e-01,
-3.36485940e+00, -3.24264437e+00,  1.94858723e+00, -1.48760393e-01,
-1.48760393e-01, -1.48760393e-01, -1.22439797e-01, -9.20638780e-01,
-4.29445645e-01, -1.84611341e+00,  4.41350368e+00,  1.44743570e+00,
-1.48760393e-01, -1.48760393e-01, -1.48760393e-01,  3.17672330e-02,
 1.37878153e-01, -1.32618603e-01,  2.20882601e-01, -6.91002117e-01,
-2.05031525e-02, -1.48760393e-01, -1.48760393e-01, -1.48760393e-01,
 1.13389600e-01,  8.67916863e-01,  5.64349997e-01,  2.75574543e+00,
-3.32265811e+00, -1.58444104e+00,  2.08273892e+00,  2.18622092e+00,
-2.02852314e+00,  1.10005306e-01,  1.05868640e-01, -1.22938339e-01,
-1.24074186e+00, -1.23515380e+00,  1.28288192e+00, -8.54871729e-14,
-1.13242749e-14, -4.32986980e-14, -7.15690269e-01, -7.86635339e-01,
 3.68908113e-02,  2.34001202e+00,  3.99790013e+00, -8.48601770e-01,
-1.48760393e-01, -1.48760393e-01, -1.48760393e-01, -1.48760393e-01,
-1.17033693e-01, -3.50870627e-01,  1.07519623e-01,  5.33245394e-01,
-6.34462692e-01,  1.06644777e+00,  6.06055298e-01, -1.69160828e+00,
-1.48760393e-01, -1.48760393e-01, -1.48760393e-01, -1.48760393e-01,
-2.33149899e-02,  2.14080413e-01, -4.45045130e-02, -2.67635320e-02,
 4.76397650e-01,  6.29695696e-01,  5.40700948e-01, -9.24102899e-01,
-1.48760393e-01, -1.48760393e-01, -1.48760393e-01, -1.48760393e-01,
 3.16897603e-01, -1.41349375e-02, -1.90821221e-01, -2.53143358e-01,
-1.99790477e+00, -1.08691507e+00, -1.57045496e+00,  2.78054243e+00,
 2.66365062e+00,  2.65850481e+00,  2.66739894e+00, -2.65055484e+00,
-8.80118936e-02, -8.24347544e-02, -1.10679953e-01,  8.67703212e-02,
-4.03816320e-01, -4.31824601e-01, -3.14663990e-01,  3.96437487e-01,
-3.17523785e-14,  1.62092562e-14, -2.98649994e-14,  2.17603713e-14,
-3.79441557e-01, -7.12657867e-01,  1.79564622e-01,  7.61302476e-01,
 2.62448112e-01, -8.98544562e-01,  9.45667919e-02, -4.62498233e-01,
-1.48760393e-01, -1.48760393e-01, -1.48760393e-01, -1.48760393e-01,
-1.48760393e-01, -3.69573799e-01, -4.13698407e-01,  1.13239005e+00,
-2.45156342e-01, -5.44315796e-01,  9.49376652e-01,  1.69307493e+00,
-4.70068902e+00, -9.38987518e-01,  2.91975550e+00, -1.48760393e-01,
-1.48760393e-01, -1.48760393e-01, -1.48760393e-01, -1.48760393e-01,
-1.10542426e-01,  2.11426621e-01, -1.84120913e-01, -1.62264554e-02,
 8.07796667e-02,  7.63924785e-01, -1.33127957e+00, -1.41430534e+00,
-1.08195940e+00,  1.43765357e+00, -1.48760393e-01, -1.48760393e-01,
-1.48760393e-01, -1.48760393e-01, -1.48760393e-01,  2.53777735e-01,
 6.11569094e-02, -9.08936296e-01,  1.15865762e-01,  4.37881421e-01,
-4.85943772e-01,  6.73858664e-01,  7.44649012e+00,  2.98742216e+00,
-6.81289537e+00, -1.37684477e+00, -1.64640277e+00, -1.56546075e+00,
-1.81046231e+00,  1.44055825e+00,  1.13495202e-01,  1.21187129e-01,
 1.35991214e-01,  1.77801935e-01, -1.17284849e-01, -9.53549904e-02,
-1.19104619e-01, -1.64111090e-01, -3.02896808e-01,  1.11545796e-01,
 5.80091530e-15, -1.33226763e-15,  1.26565425e-14, -5.32907052e-15,
 6.69603262e-15, -1.71111043e-02, -4.31129795e-01,  8.54122193e-01,
-2.04420416e-01, -5.79524192e-01, -6.89687791e-01,  2.52517627e+00,
-1.33413629e+00, -9.11990196e-02,  8.68699261e-01, -1.48760393e-01,
-1.48760393e-01, -1.48760393e-01, -1.48760393e-01, -1.48760393e-01,
-2.68845444e-01, -4.30198881e-01, -8.09855452e-01,  5.15595154e-01,
 3.71544952e-01,  2.29458350e+00,  2.46001943e+00,  4.05058079e+00,
```

```
-1.50003270e+00, -2.84399717e+00, -1.48760393e-01, -1.48760393e-01,
-1.48760393e-01, -1.48760393e-01, -1.48760393e-01,  7.03519969e-03,
-7.25624041e-02,  1.98796634e-01, -3.07641675e-02, -1.08718149e-01,
-3.99784656e-01, -1.23347457e-01,  2.61781404e-01,  6.70140867e-01,
-1.70499938e-01, -1.48760393e-01, -1.48760393e-01, -1.48760393e-01,
-1.48760393e-01, -1.48760393e-01,  5.86854001e-01,  4.22347144e-01,
 6.62088394e-01, -1.86258510e-01, -4.58021734e-01, -3.24426286e+00,
-2.56458123e+00, -5.96989635e+00, -2.53422546e-01,  5.30742409e+00,
 5.05152213e-01,  5.78096564e-01,  3.89240524e-01,  6.26597780e-01,
-3.50714541e-01, -9.69596369e-02, -9.48210783e-02, -8.78706361e-02,
-1.15754293e-01,  8.14079268e-02,  3.33510099e-01,  3.70735829e-01,
 3.19555166e-01,  4.19383341e-01, -3.08197800e-01, -8.88178420e-16,
 0.00000000e+00,  3.10862447e-15, -3.77475828e-15, -1.33226763e-15,
-1.99070463e-01,  1.25050175e-01, -5.04444050e-01,  5.06474401e-01,
 3.82348449e-02,  2.19918105e+00,  1.19021973e+00,  1.61582891e+00,
-2.16726845e+00, -8.94120871e-01, -1.48760393e-01,  9.33433484e-01,
-2.46596863e+00, -1.48760393e-01, -4.43811363e-01,  5.91878118e-01,
-1.48760393e-01, -1.14077106e+00,  2.18176411e+00, -2.34762466e+00,
 1.65298362e-01, -8.15424772e-02,  0.00000000e+00,  1.16371907e+00,
 1.35341950e-01, -1.48760393e-01, -1.94399739e-02,  2.39253097e+00,
-1.48760393e-01,  8.96549189e-02,  8.85652794e-01, -1.48760393e-01,
 1.38956986e-01, -3.21611261e+00, -1.15765211e+00,  1.69119867e-03,
 3.05248060e-01,  0.00000000e+00, -2.71598848e-01,  1.88633632e+00,
-1.48760393e-01, -1.36075873e-01, -3.31376252e+00, -1.48760393e-01,
-6.35789860e-02,  1.34656102e+00, -1.48760393e-01,  2.50974719e-01,
 2.69207013e+00,  2.31366120e+00,  1.00786138e-01, -1.25805647e+00,
 0.00000000e+00,  1.72419164e-01, -5.60703566e+00, -1.48760393e-01,
 7.79090694e-01, -1.00211327e+00, -1.48760393e-01,  1.73270799e-01,
-1.38140334e+00, -1.48760393e-01, -1.15770623e+00,  2.04440461e+00,
 2.16136467e+00, -2.87131010e-02, -5.52172746e-01,  0.00000000e+00,
 7.53421935e-02,  2.47762726e+00, -1.48760393e-01,  8.44966709e-01,
 7.30641236e-01, -1.48760393e-01,  4.05826464e-03, -3.63405248e-02,
-1.48760393e-01, -7.38617825e-01, -1.53793510e+00, -8.27014282e-01,
-3.97980927e-02,  5.59548517e-01,  0.00000000e+00,  7.26728373e-01,
 1.23617094e+00, -1.48760393e-01,  8.36611784e-01, -4.70918669e+00,
-1.48760393e-01, -2.49362165e-01,  9.43478171e-01, -1.48760393e-01,
-7.02875995e-01,  5.00561668e+00, -1.57273582e+00,  4.92869140e-02,
 1.77723583e-01,  0.00000000e+00,  8.96051179e-01, -5.01175561e+00,
-1.48760393e-01,  2.65063958e-01, -3.83080933e-01, -1.48760393e-01,
 5.09553565e-02,  8.35719221e-01, -1.48760393e-01, -2.39717421e-01,
-4.79719337e-01,  2.12053206e+00,  1.27340988e-01, -1.32746825e+00,
 0.00000000e+00, -8.11836185e-02, -5.24474048e-02, -1.48760393e-01,
 3.24389840e-01,  7.88814318e-02, -1.48760393e-01,  1.65148631e-01,
-4.13702407e-01, -1.48760393e-01, -1.30164145e-01, -1.14939492e+00,
-6.19870349e-01, -6.10749375e-02,  6.09387869e-01,  0.00000000e+00,
 2.40205003e-01,  4.95726094e-01])
```

Juntamos todas las funciones para predecir con todos los chunks

In [39]:
```
%%time
number = 1

for chunk in iterator:

    print(f'Model number {number}')

    chunk = data_filter(chunk)
    chunk = dates(chunk)
    chunk = hours_catalog(chunk)
```

```
    hri,hrf = chunk[['id_hour']].describe().T[['min','max']].values[0].tolist()
    vobs = 24
    vdes = 1
    anclai = int(hri)+vobs-1
    anclaf = int(hrf)-vdes
    um = ['PULocationID', 'ancla']
    ancla = 24
    step = 4
    varc = ['trip_distance', 'total_amount', 'n']
    vard = ['hora']

    print(f'Hra inicial: {hri}, Modelo: {number}')
    print(f'Hra final: {hrf}, Modelo: {number}')

    X = pd.concat(map(lambda ancla:reduce(lambda x,y:pd.merge(x,y,on=um,how='out
           map(lambda k:trans(chunk,ancla,k),range(step,vobs+step,step))),range(
    y= pd.concat(map(lambda ancla: target(chunk,ancla,vdes),range(anclai,anclaf+

    tad = TAD(X, y, um)
    varc = [v for v in tad.columns if v[:2]=="v_"]
    tgt = 'y'

    miss = 1-tad[varc].describe().T[['count']]/len(tad)

    X, Xi = impute(tad, varc)

    extreme(X, um, tad)


    regression(tad, tgt, Xi)

    number += 1
```

```
Model number 1
Hra inicial: 1.0, Modelo: 1
Hra final: 112.0, Modelo: 1
                          variable        ks
3     v_hora_min_total_amount_1_4  0.294406
4     v_hora_min_total_amount_2_4  0.316723
6    v_hora_min_trip_distance_1_4  0.312624
7    v_hora_min_trip_distance_2_4  0.323951
12    v_hora_max_total_amount_1_4  0.312452
..                            ...       ...
444             v_hora_sum_n_0_8  0.266582
445   v_hora_sum_total_amount_0_8  0.266818
446  v_hora_sum_trip_distance_0_8  0.266700
448   v_hora_std_total_amount_0_8  0.288464
449  v_hora_std_trip_distance_0_8  0.288464

[156 rows x 2 columns]
count    9722.000000
mean        0.358465
std         0.479574
min         0.000000
25%         0.000000
50%         0.000000
75%         1.000000
max         1.000000
Name: extremo, dtype: float64
Fitting 10 folds for each of 4 candidates, totalling 40 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:    3.9s finished
```

```
14   v_hora_mean_total_amount_0_4  0.345952
..                            ...       ...
444             v_hora_sum_n_3_4  0.341100
445   v_hora_sum_total_amount_3_4  0.341568
446  v_hora_sum_trip_distance_3_4  0.341568
448   v_hora_std_total_amount_3_4  0.351450
449  v_hora_std_trip_distance_3_4  0.351450

[164 rows x 2 columns]
count    9209.000000
mean        0.404061
std         0.490736
min         0.000000
25%         0.000000
50%         0.000000
75%         1.000000
max         1.000000
Name: extremo, dtype: float64
Fitting 10 folds for each of 4 candidates, totalling 40 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:    2.9s finished
18.75571170775452
20.830105257517218
Model number 112
Hra inicial: 1.0, Modelo: 112
Hra final: 30.0, Modelo: 112
                            variable        ks
3       v_hora_min_total_amount_2_4  0.195548
6      v_hora_min_trip_distance_2_4  0.225138
12      v_hora_max_total_amount_2_4  0.225138
15     v_hora_max_trip_distance_2_4  0.225138
21     v_hora_mean_total_amount_2_4  0.225138
24    v_hora_mean_trip_distance_2_4  0.225138
27                v_hora_sum_n_2_4  0.225138
30      v_hora_sum_total_amount_2_4  0.225138
33     v_hora_sum_trip_distance_2_4  0.225138
39      v_hora_std_total_amount_2_4  0.249995
42     v_hora_std_trip_distance_2_4  0.249995
49      v_hora_min_total_amount_1_8  0.385702
53     v_hora_min_trip_distance_1_8  0.409316
61      v_hora_max_total_amount_1_8  0.417187
65     v_hora_max_trip_distance_1_8  0.417187
73     v_hora_mean_total_amount_1_8  0.417187
77    v_hora_mean_trip_distance_1_8  0.417187
81                v_hora_sum_n_1_8  0.417187
85      v_hora_sum_total_amount_1_8  0.417187
89     v_hora_sum_trip_distance_1_8  0.417187
97      v_hora_std_total_amount_1_8  0.422749
101    v_hora_std_trip_distance_1_8  0.422749
170    v_hora_min_total_amount_0_16  0.231921
175   v_hora_min_trip_distance_0_16  0.237683
185    v_hora_max_total_amount_0_16  0.237683
190   v_hora_max_trip_distance_0_16  0.239123
200   v_hora_mean_total_amount_0_16  0.239123
205  v_hora_mean_trip_distance_0_16  0.239123
210               v_hora_sum_n_0_16  0.239123
215    v_hora_sum_total_amount_0_16  0.239123
220   v_hora_sum_trip_distance_0_16  0.239123
230    v_hora_std_total_amount_0_16  0.275000
235   v_hora_std_trip_distance_0_16  0.275000
count    640.000000
mean       0.325000
std        0.468741
min        0.000000
25%        0.000000
```

```
50%        0.000000
75%        1.000000
max        1.000000
Name: extremo, dtype: float64
Fitting 10 folds for each of 4 candidates, totalling 40 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=-1)]: Done  40 out of  40 | elapsed:    0.2s finished
15.399852347320953
38.200627576156414
CPU times: user 7h 51min 52s, sys: 5min 39s, total: 7h 57min 32s
Wall time: 7h 52min 21s
```

Persistencia de los Modelos

In [40]:
```
import pickle
```

In [45]:
```
with open("models_other.pkl", "wb") as f:
    for model in models:
         pickle.dump(model, f)
```

Si queremos abrir los modelos de nuevo para evitar entrenamiento

In [42]:
```
new_models = []
with open("models.pckl", "rb") as f:
    while True:
        try:
            new_models.append(pickle.load(f))
        except EOFError:
            break
```

In [44]:
```
len(new_models)
```

Out[44]:
```
112
```

In [ ]:
```

```

Anexo Modelo No Supervisado

January 11, 2021

1 Clustering Model

1.1 Libraries

[1]:
```
import pandas as pd
import dask.dataframe as dd
import numpy as np
import random

from sklearn.preprocessing import StandardScaler,MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE,MDS
from sklearn.cluster import AgglomerativeClustering,KMeans
from sklearn.mixture import GaussianMixture

from scipy.stats import kruskal

from sklearn.feature_selection import SelectKBest

import matplotlib.pyplot as plt
import seaborn as sns
```

1.2 Data Loading

[2]:
```
csv = '2018_Yellow_Taxi_Trip_Data.csv'

fields = ['passenger_count', 'trip_distance', 'tip_amount',
          'total_amount', 'PULocationID', 'DOLocationID']
```

[72]:
```
temp =dd.read_csv(csv,
                  usecols=fields,
                  dtype={'passenger_count':'int8', 'trip_distance':'float32',
                         'total_amount':'float32', 'PULocationID': 'int16',
                         'DOLocationID':'int16', 'tip_amount': 'float16'})
```

[78]:
```
temp.describe(percentiles=(0.01,0.99)).compute().T[['min','1%','99%','max']]
```

[78]:

	min	1%	99%	max
passenger_count	-64.000000	1.0	6.000000	96.00000
trip_distance	0.000000	0.2	19.629999	189483.84375
PULocationID	1.000000	13.0	264.000000	265.00000
DOLocationID	1.000000	13.0	264.000000	265.00000
tip_amount	-322.500000	0.0	13.046875	946.00000
total_amount	-800.299988	4.8	75.669998	907071.06250

1.2.1 Vamos a predecir el numero de pasajeros.

Tiramos los que tengan 0, 7,8 y 9 pasajeros

[4]:
```
temp = temp[temp['passenger_count'] > 0]
temp = temp[temp['passenger_count'] < 7]
temp = temp[temp['trip_distance'] > 0]
temp = temp[temp['total_amount'] > 0]
```

[5]:
```
df = temp.sample(frac=0.000008).compute()
```

[6]:
```
df.describe()
```

[6]:

	passenger_count	trip_distance	PULocationID	DOLocationID	tip_amount	\
count	815.000000	815.000000	815.000000	815.000000	815.000000	
mean	1.592638	2.939276	161.150920	157.980368	1.917969	
std	1.205412	3.818235	67.278825	71.961135	2.480469	
min	1.000000	0.070000	4.000000	1.000000	0.000000	
25%	1.000000	0.920000	113.000000	107.000000	0.000000	
50%	1.000000	1.570000	162.000000	162.000000	1.450195	
75%	2.000000	3.110000	233.000000	233.000000	2.455078	
max	6.000000	34.900002	264.000000	265.000000	25.546875	

	total_amount
count	815.000000
mean	16.325069
std	13.937790
min	3.300000
25%	8.300000
50%	11.800000
75%	18.299999
max	153.350006

[7]:
```
df.describe(percentiles=[0.001, 0.01, 0.99]).T[['0.1%', '1%', '99%']]
```

[7]:

	0.1%	1%	99%
passenger_count	1.00000	1.0	6.000000
trip_distance	0.09442	0.3	18.647400
PULocationID	6.44200	13.0	264.000000
DOLocationID	1.00000	7.0	264.000000
tip_amount	0.00000	0.0	11.703125
total_amount	3.70700	4.8	69.197600

1.3 Visualization

[8]:
```
varc = [v for v in df.columns if v != "passenger_count"]
varc
```

[8]:
```
['trip_distance', 'PULocationID', 'DOLocationID', 'tip_amount', 'total_amount']
```

[9]:
```
X = df[varc].copy()
```

1.3.1 PCA

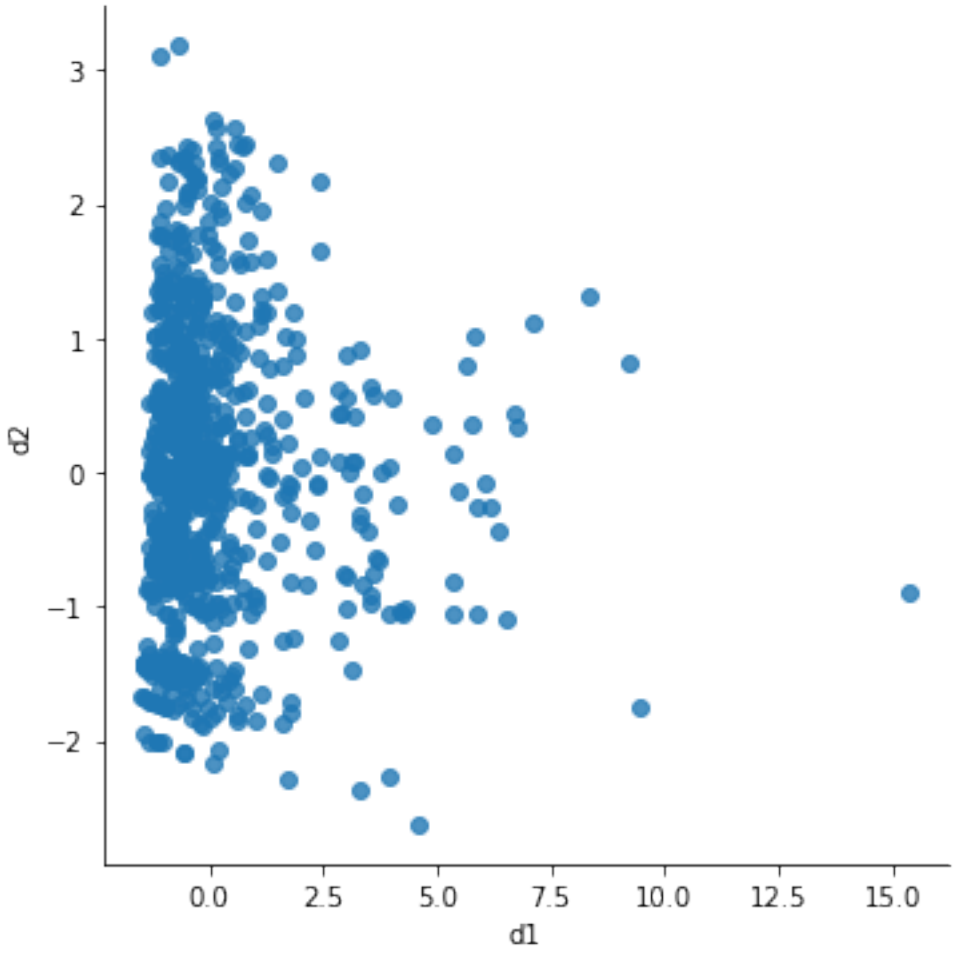
[10]:
```
sc = StandardScaler()
sc.fit(X)
Xs = pd.DataFrame(sc.transform(X),columns=varc)
pca = PCA(n_components=2)
pca.fit(Xs)
pca.explained_variance_ratio_.cumsum()
```

[10]:
```
array([0.5179963 , 0.74349976], dtype=float32)
```

[11]:
```
Xp = pd.DataFrame(pca.transform(Xs),columns=['d1','d2'])
```

[12]:
```
sns.lmplot(data=Xp,x='d1',y='d2',fit_reg=False)
```

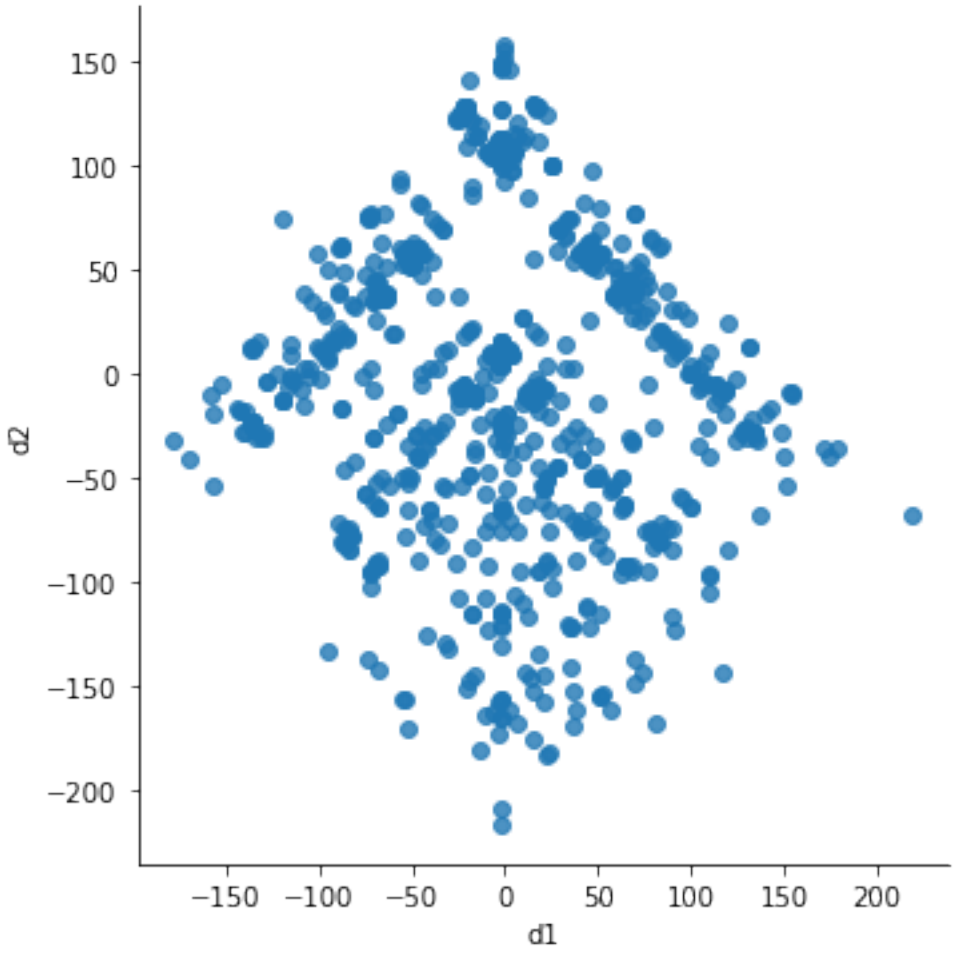
[12]:
```
<seaborn.axisgrid.FacetGrid at 0x7f574c407550>
```



1.3.2 MDS

[13]:
```
mds = MDS(n_components=2,n_jobs=-1)
Xm = pd.DataFrame(mds.fit_transform(X),columns=['d1','d2'])
sns.lmplot(data=Xm,x='d1',y='d2',fit_reg=False)
```

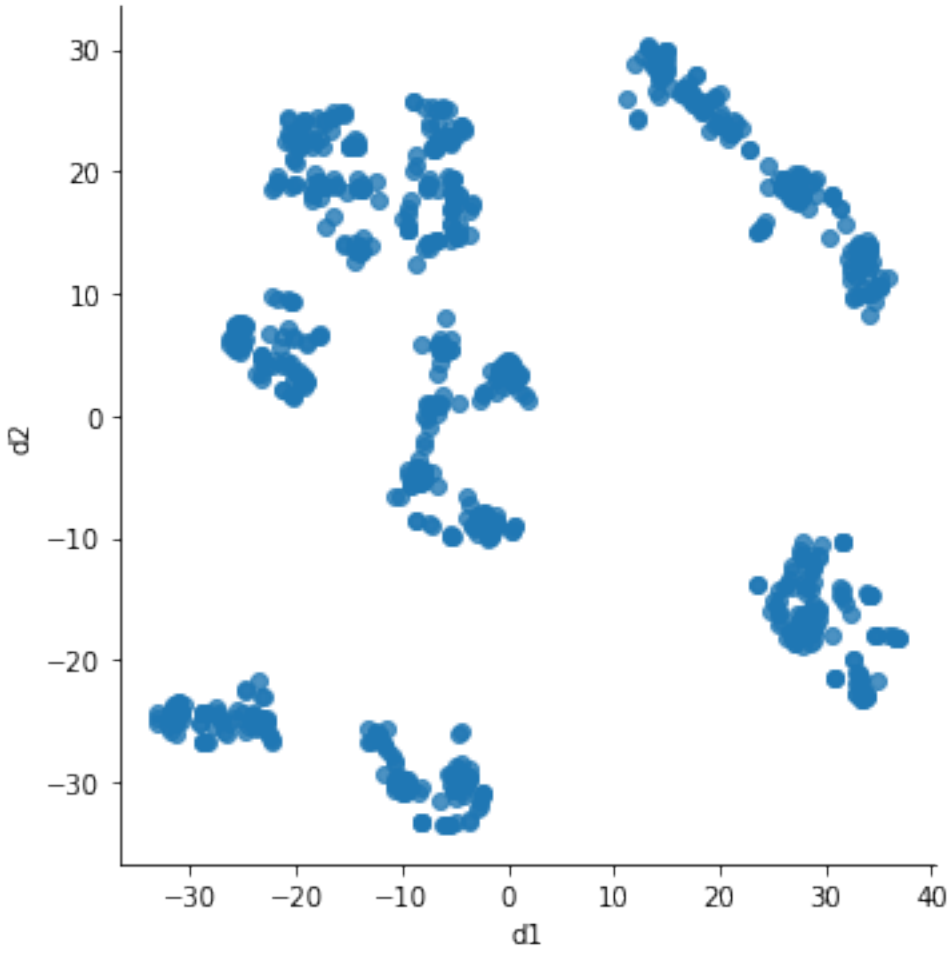
[13]: <seaborn.axisgrid.FacetGrid at 0x7f574c3175f8>



1.3.3 T-SNE

[14]:
```
tsne = TSNE(n_components=2,n_jobs=-1)
Xt = pd.DataFrame(tsne.fit_transform(X),columns=['d1','d2'])
sns.lmplot(data=Xt,x='d1',y='d2',fit_reg=False)
```

[14]:
```
<seaborn.axisgrid.FacetGrid at 0x7f574c2dfa58>
```



1.4 Exploratory Analysis

[15]:
```
X.describe(percentiles=np.arange(0,1,0.1))
```

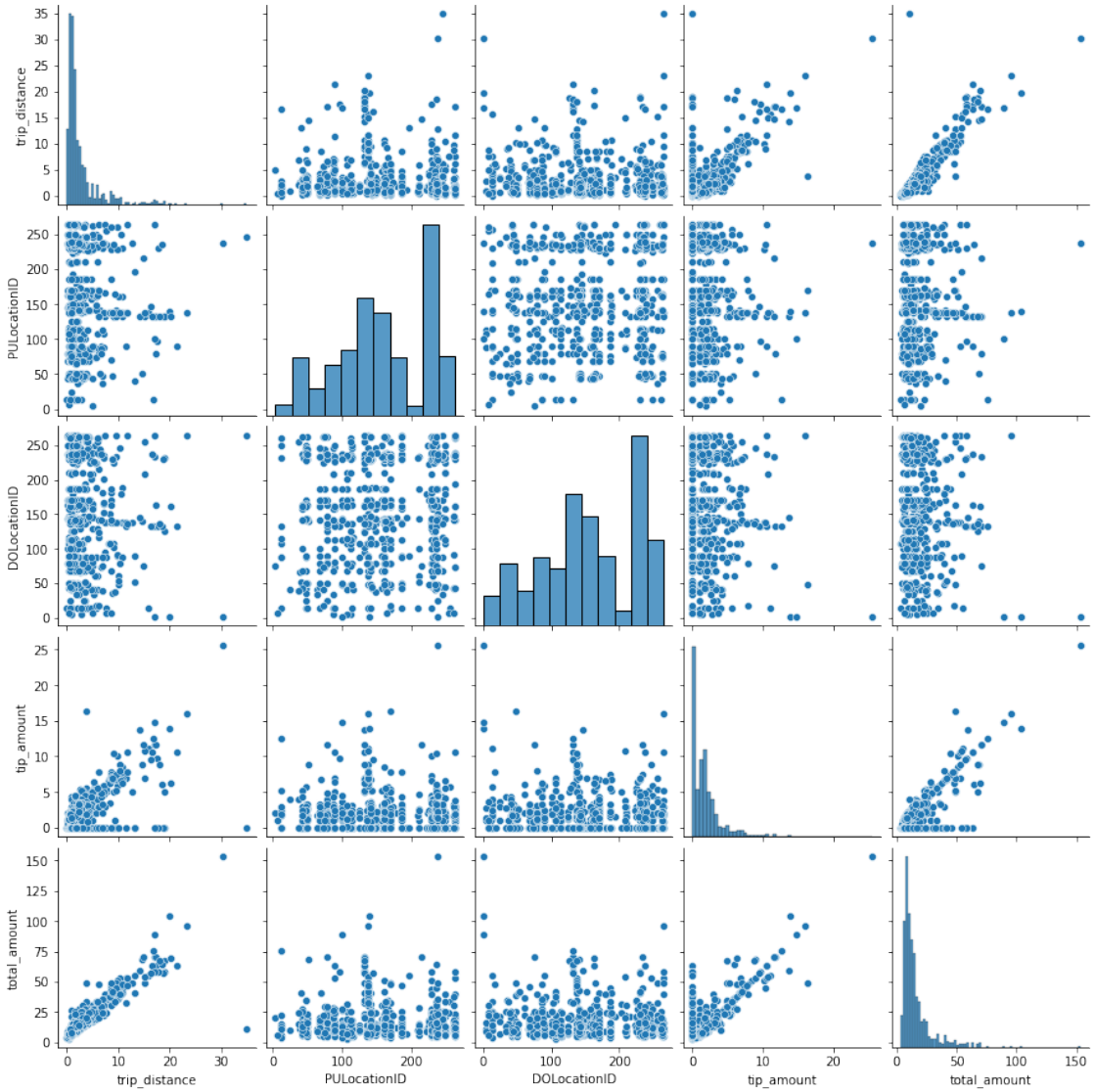
[15]:

	trip_distance	PULocationID	DOLocationID	tip_amount	total_amount
count	815.000000	815.000000	815.000000	815.000000	815.000000
mean	2.939276	161.150920	157.980368	1.917969	16.325069
std	3.818235	67.278825	71.961135	2.480469	13.937790
min	0.070000	4.000000	1.000000	0.000000	3.300000
0%	0.070000	4.000000	1.000000	0.000000	3.300000
10%	0.600000	68.000000	48.000000	0.000000	6.368000
20%	0.818000	100.000000	87.000000	0.000000	7.850000
30%	1.040000	132.000000	125.000000	0.000000	8.800000
40%	1.296000	141.000000	142.000000	1.000000	10.300000
50%	1.570000	162.000000	162.000000	1.450195	11.800000
60%	1.918000	170.000000	170.000000	1.781641	13.800000

70%	2.600000	230.000000	230.000000	2.160156	16.000000
80%	3.700000	236.000000	236.000000	2.951563	20.768000
90%	7.108000	239.000000	241.400000	4.558594	32.016000
max	34.900002	264.000000	265.000000	25.546875	153.350006

[16]:
```
sns.pairplot(X)
```

[16]: <seaborn.axisgrid.PairGrid at 0x7f574c2c6d68>



[17]:
```
X.corr()
```

[17]:

	trip_distance	PULocationID	DOLocationID	tip_amount	\
trip_distance	1.000000	-0.034582	-0.089966	0.644051	

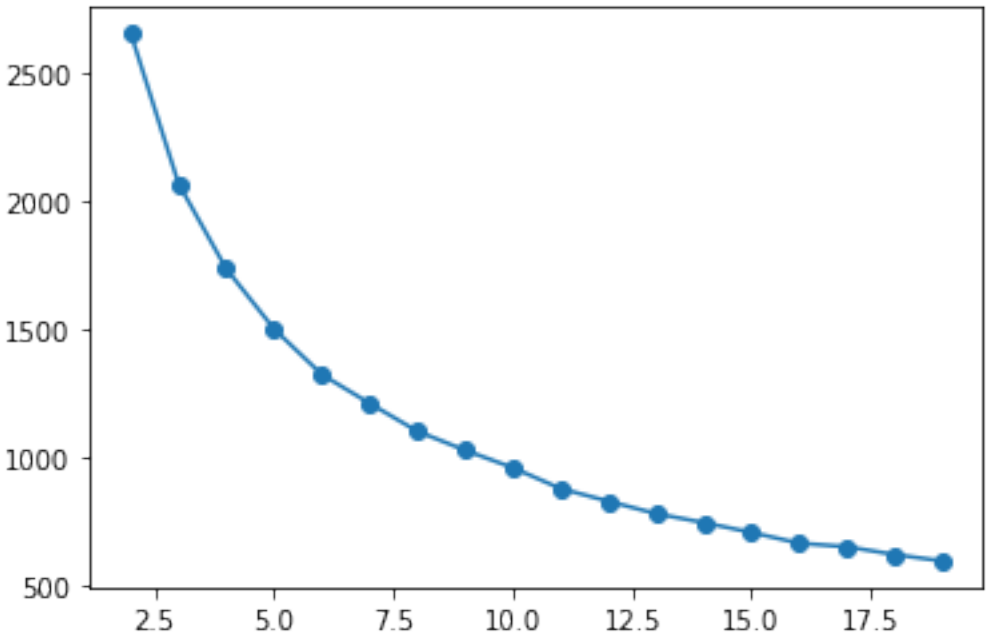
```
PULocationID       -0.034582      1.000000      0.141475   -0.020398
DOLocationID       -0.089966      0.141475      1.000000   -0.061298
tip_amount          0.644051     -0.020398     -0.061298    1.000000
total_amount        0.907124     -0.039812     -0.112205    0.799711
```

```
               total_amount
trip_distance      0.907124
PULocationID      -0.039812
DOLocationID      -0.112205
tip_amount         0.799711
total_amount       1.000000
```

1.4.1 # of Clusters

[18]:
```
l = []
for k in range(2,20):
    cl = KMeans(n_clusters=k)
    cl.fit(Xs)
    l.append(cl.inertia_)
plt.plot(range(2,20),l,marker='o')
```

[18]: [<matplotlib.lines.Line2D at 0x7f5768fc6240>]



[19]:
```
k = 7
```

[20]:
```
varc = X.columns.tolist()
varc
```

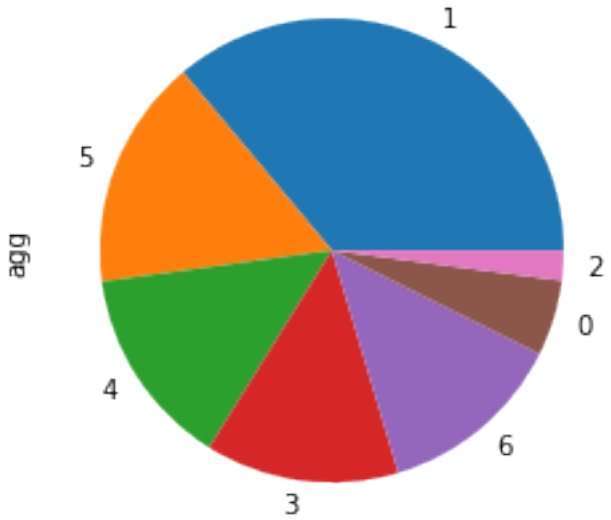
[20]: ['trip_distance', 'PULocationID', 'DOLocationID', 'tip_amount', 'total_amount']

1.5 Modelo no supervisado (Aglomerativo)

[21]:
```
cl = 'agg'
agg = AgglomerativeClustering(n_clusters=k)
X[cl]=Xs[cl]=Xm[cl]=Xt[cl]=Xp[cl]=df[cl] = agg.fit_predict(Xs[varc])
display(df[cl].value_counts(True).sort_index())
df[cl].value_counts().plot(kind='pie')
```

```
0    0.052761
1    0.360736
2    0.020859
3    0.134969
4    0.139877
5    0.160736
6    0.130061
Name: agg, dtype: float64
```

[21]: <AxesSubplot:ylabel='agg'>

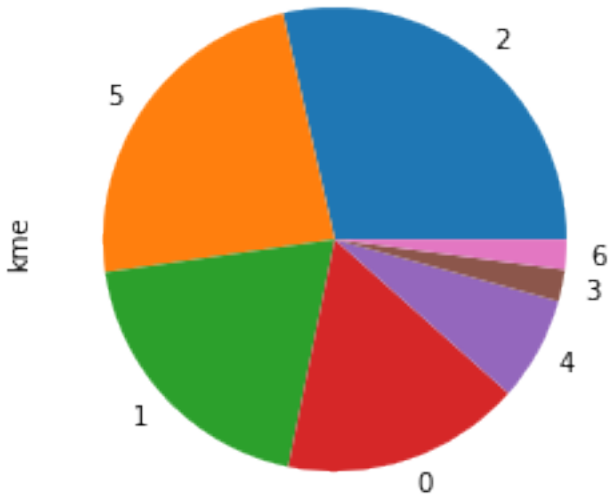


1.6 K-Means

[22]:
```
cl = 'kme'
agg = KMeans(n_clusters=k)
X[cl]=Xs[cl]=Xm[cl]=Xt[cl]=Xp[cl]=df[cl] = agg.fit_predict(Xs[varc])
display(df[cl].value_counts(True).sort_index())
df[cl].value_counts().plot(kind='pie')
```

```
0    0.166871
1    0.195092
2    0.285890
3    0.022086
4    0.072393
5    0.236810
6    0.020859
Name: kme, dtype: float64
```

[22]: <AxesSubplot:ylabel='kme'>

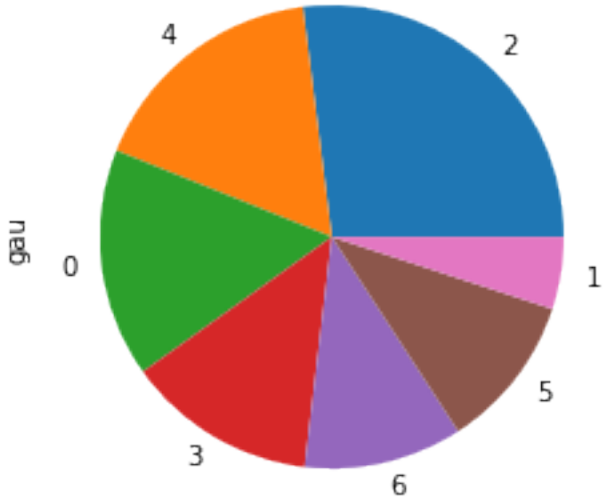


1.7 Gaussian Mixture

[23]:
```
cl = 'gau'
agg = GaussianMixture(n_components=k)
X[cl]=Xs[cl]=Xm[cl]=Xt[cl]=Xp[cl]=df[cl] = agg.fit_predict(Xs[varc])
display(df[cl].value_counts(True).sort_index())
df[cl].value_counts().plot(kind='pie')
```

```
0    0.159509
1    0.050307
2    0.269939
3    0.132515
4    0.169325
5    0.107975
6    0.110429
Name: gau, dtype: float64
```

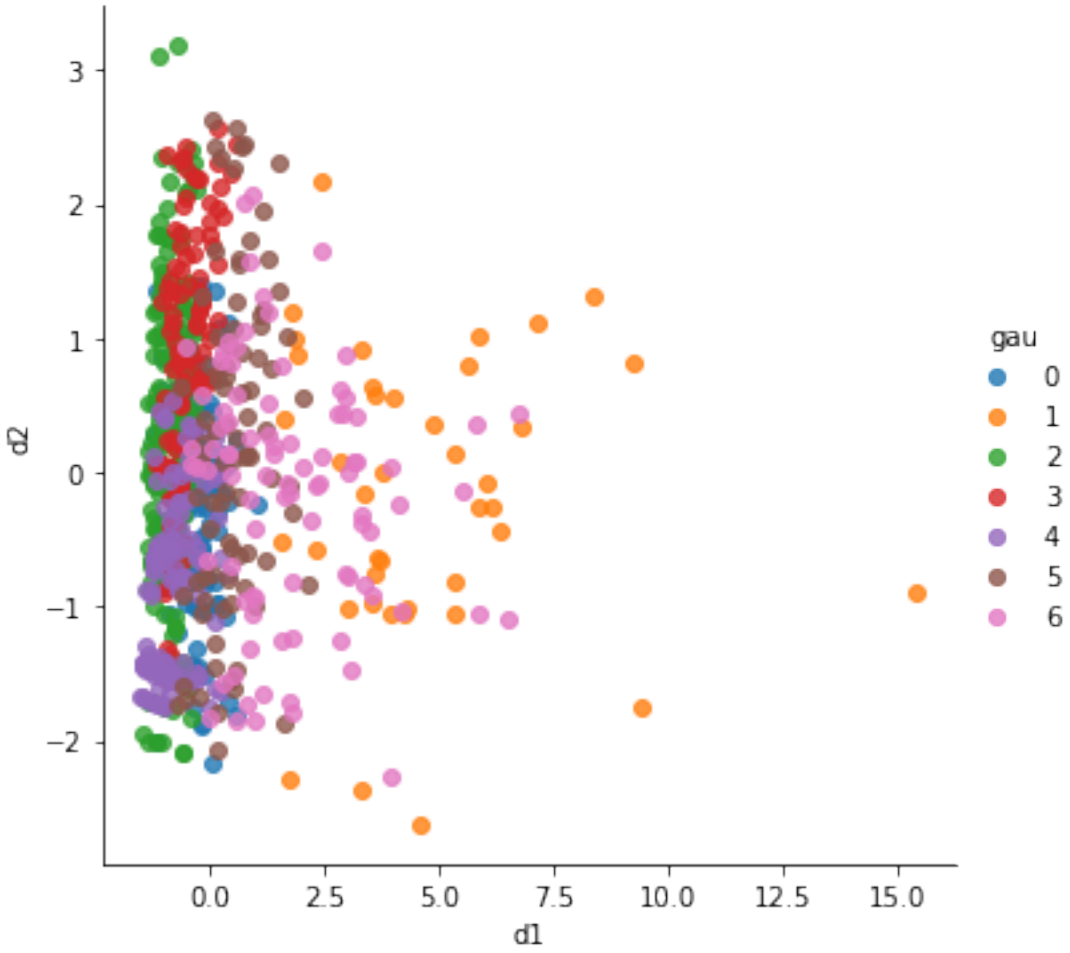
[23]: <AxesSubplot:ylabel='gau'>

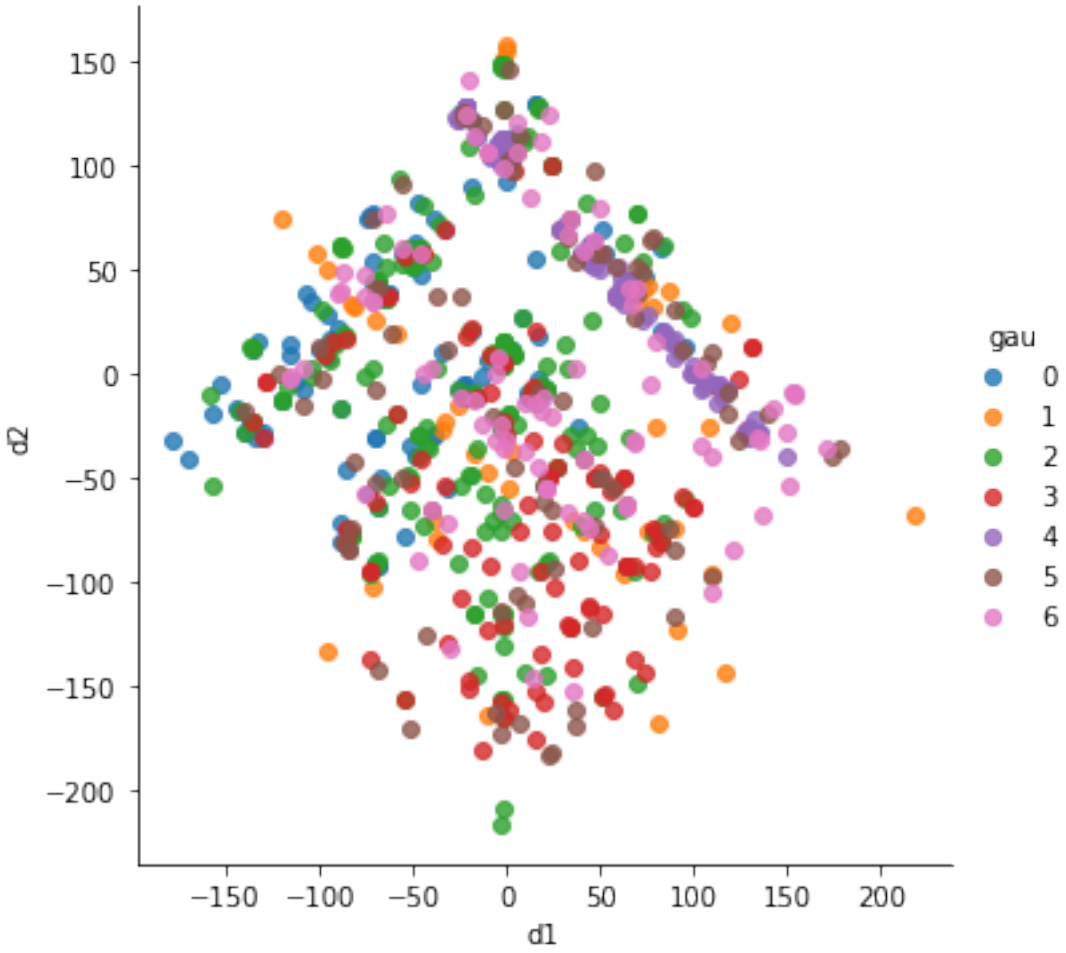


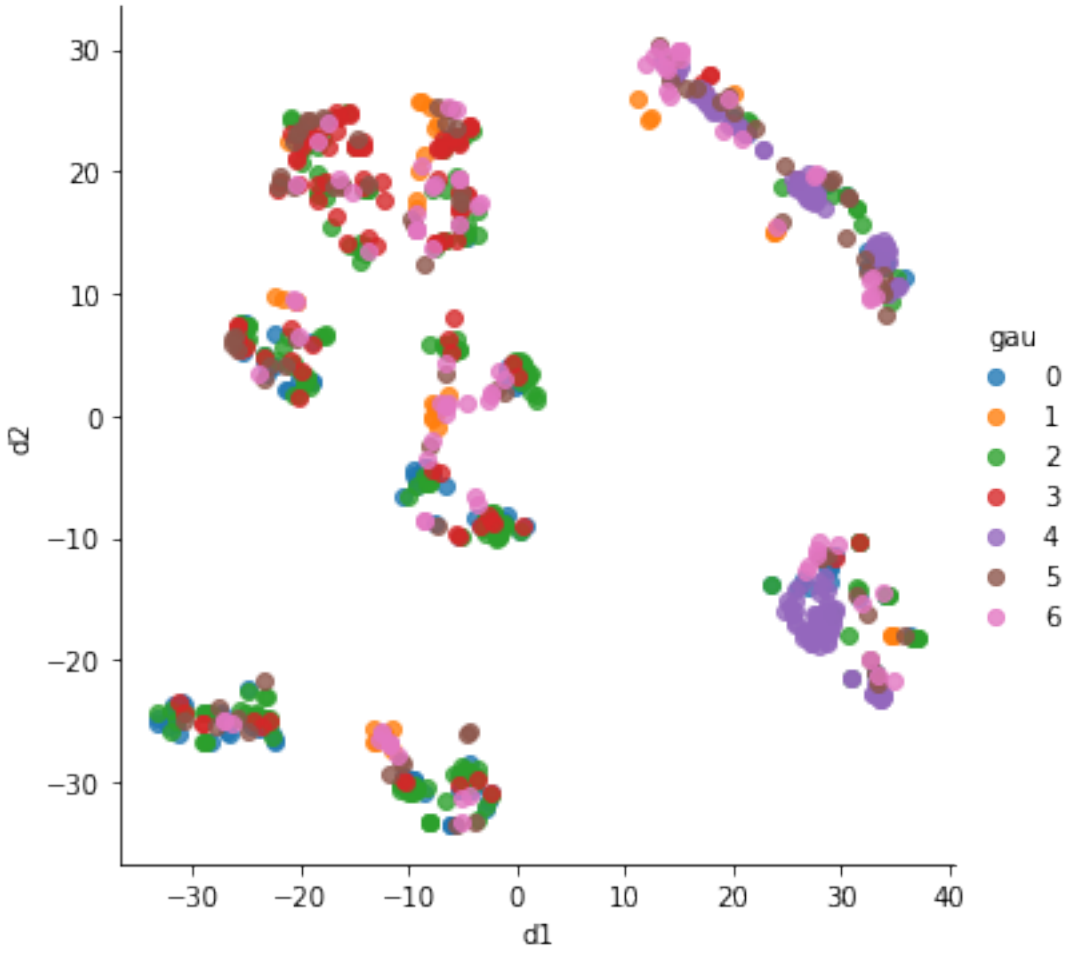
1.8 2D Visualization

[24]:
```
sns.lmplot(data=Xp,x='d1',y='d2',fit_reg=False,hue='gau')
sns.lmplot(data=Xm,x='d1',y='d2',fit_reg=False,hue='gau')
sns.lmplot(data=Xt,x='d1',y='d2',fit_reg=False,hue='gau')
```

[24]: <seaborn.axisgrid.FacetGrid at 0x7f577ab21588>


3
2
1
0
−1
−2
d2
0.0
2.5
5.0
7.5
10.0
12.5
15.0
d1
gau
0
1
2
3
4
5
6


150
100
50
0
−50
−100
−150
−200
d2
−150
−100
−50
0
50
100
150
200
d1
gau
0
1
2
3
4
5
6



1.9 Perfilamiento

$p - value < \alpha$ Son diferentes y por tanto la variable sirve para perfilar

[25]:
```
pd.DataFrame(map(lambda v:(v,kruskal(*[d[v].tolist() for _,d in df.
↪groupby('gau')]).pvalue),
      varc),columns=['variable','p-value'])
```

[25]:

	variable	p-value
0	trip_distance	2.843500e-109
1	PULocationID	1.830534e-42
2	DOLocationID	1.184611e-25
3	tip_amount	3.332350e-60
4	total_amount	1.057493e-129

[26]:
```
sk = SelectKBest(k='all')
sk.fit(X[varc],X['gau'])
```

[26]:
```
SelectKBest(k='all')
```

[27]:
```
best = [v for v,x in zip(varc,sk.get_support()) if x]
best
```

[27]:
```
['trip_distance', 'PULocationID', 'DOLocationID', 'tip_amount', 'total_amount']
```

1.10 Examples

[64]:
```
k = 5
cl = 2
for id in df.loc[df['gau']==cl].sample(k).DOLocationID:
    print(id)
```

```
140
142
246
224
238
```

[69]:
```
i = 5
cluster = 4
for id in df.loc[df['gau']==cluster].sample(i).trip_distance:
    print(id)
```

```
0.699999988079071
1.2999999523162842
0.4699999988079071
0.6000000238418579
0.49000000953674316
```

2 Persistencia

[71]:
```
import pickle
pickle.dump((sc, agg),open('gaussian cluster_midterm.pkl','wb'))
```