Take-Home test 1Q22

Roberto Vásquez Martínez

February 20, 2022

1 Take Home test Nu MX 2022

1.1 Data Wrangling + Exploration

In the next code cell, we charge the datasets that help us in the first section. We wil use pandas Python library in order to manipulate the datasets.

[1]:
```
import pandas as pd
magic_towns=pd.read_csv('pueblos_magicos.csv')
mexico_tourism=pd.read_csv('turismo_mexico.csv')
```

We show a preview of the data sets. Firstly, we show the head of `pueblos_magicos.csv`.

[2]:
```
magic_towns.head()
```

[2]:
```
        pueblo_magico                estado  pob_2010  pob_2015
0            Asientos        Aguascalientes     48358     50864
1            Calvillo        Aguascalientes     57627     60760
2  San José de Gracia        Aguascalientes      7160      9661
3              Tecate       Baja California     89999    110870
4              La Paz   Baja California Sur    265717    293687
```

Then, we show the head of `turismo_mexico.csv` dataset.

[3]:
```
mexico_tourism.head()
```

[3]:
```
      fecha  visitantes_internacionales  turismo_al_interior  \
0  01/01/16                        7808                 1690
1  01/02/16                        7666                 1683
2  01/03/16                        8625                 1983
3  01/04/16                        7717                 1601
4  01/05/16                        7665                 1548

   turismo_fronterizo  excursionistas _fronterizos  pasajeros_crucero
0                1152                         4332                634
1                1048                         4250                685
2                1224                         4678                739
3                1083                         4451                582
4                1154                         4538                424
```

1.1.1 Exploratory Data Analysis

In the following we are going to answer a pair of questions using the datasets.

What were the ten Pueblos mágicos with the most population in 2015? In order to answer this question we sort the dataset by that column storing that information in a new variable, and then we obtain the firts then rows corresponding to ten Pueblos máxicos with de most population in 2015.

[4]:
```
pob_2015_magic_towns=magic_towns.sort_values(['pob_2015'],ascending=False)
pob_10_towns_most=pob_2015_magic_towns['pueblo_magico'][:10]
print(pob_10_towns_most)
```

```
44                   Tlaquepaque
4                         La Paz
48                       Metepec
18        San Cristóbal de las Casas
117                    Guadalupe
113                     Papantla
15            Comitán de Domínguez
37                Lagos de Moreno
81              San Andrés Cholula
67      Bahía de Banderas (Sayulita)
Name: pueblo_magico, dtype: object
```

The last list shows the 10 Pueblos mágicos with the most population in 2015.

What were the ten Pueblos mágicos with de least population in 2010? We do the same, store in a variable the dataframe of Pueblos mágicos ordered in base of `pob_2010` column, then we print the registers of interest.

[5]:
```
pob_2010_magic_towns=magic_towns.sort_values(['pob_2010'])
pob_10_towns_least=pob_2010_magic_towns['pueblo_magico'][:10]
print(pob_10_towns_least)
```

```
72                    Capulálpam de Méndez
8                                  Candela
10                                Guerrero
68                              Bustamante
105                                   Mier
74      San Pedro y San Pablo Teposcolula
122                Teúl de González Ortega
40                 San Sebastián del Oeste
2                      San José de Gracia
33                       Mineral del Chico
Name: pueblo_magico, dtype: object
```

These are the ten Pueblos mágicos with the least population in 2010.

1.1.2 Data Wrangling

We create a `DataFrame` with the table in the exam's PDF containing the Full name and the corresponding ISO code.

[6]:
```
df_estado_iso=pd.read_csv('estado_iso.csv')
df_estado_iso.sort_values(['Full name'],inplace=True)
df_estado_iso.head()
```

[6]:
```
            Full name 3-letter-code
0       Aguascalientes           AGU
1      Baja California           BCN
2  Baja California Sur           BCS
3             Campeche           CAM
6              Chiapas           CHP
```

First of all, we are going to check if the data in `Full name` is equal to the set of states storing in `estado` column in the original `pueblos_magicos.csv`. In the next cell, we charge the different registers of `df_estado_iso` and `pueblos_magicos.csv`and check if the two list of states are equal

[7]:
```
states_full_name=df_estado_iso['Full name'].to_list()
states_full_name.sort()
states_original=list(set(magic_towns['estado']))
states_original.sort()
print(states_full_name==states_original)
```

```
False
```

The last result is `False`, then we are going to check the set of states in the original data set `pueblos_magicos.csv`.

[8]:
```
states_original
```

[8]:
```
['Aguascalientes',
 'Baja California',
 'Baja California Sur',
 'Campeche',
 'Chiapas',
 'Chihuahua',
 'Coahuila',
 'Colima',
 'Durango',
 'Guanajuato',
 'Guerrero',
 'Hidalgo',
 'Jalisco',
 'Mexico',
 'Michoacan',
 'Morelos',
```

```
 'Nayarit',
 'Nuevo Leon',
 'Oaxaca',
 'Puebla',
 'Queretaro',
 'Quintana Roo',
 'San Luis Potosi',
 'Sinaloa',
 'Sonora',
 'Tabasco',
 'Tamaulipas',
 'Tlaxcala',
 'Veracruz',
 'Yucatan',
 'Zacatecas',
 'Zacatezas']
```

We can see a problem with a typo in Zacatecas spelling, therefore exists a row with a state `Zacatezas` instead of `Zacatecas`. We are going to repair that mistake in the dataset. We will replace `Zacatezas` with `Zacatecas` and then check if the set of states of the setting dataset is equal to the list of states in the table `df_estado_iso`.

[9]:
```
magic_towns.loc[magic_towns['estado']=='Zacatezas','estado']='Zacatecas'
states_original_correct=list(set(magic_towns['estado']))
states_original_correct.sort()
print(states_original_correct==states_full_name)
```

```
True
```

Finally, with the same set of states in the original dataset and `df_estado_iso` we can set the `estado` column with the corresponding ISO code using a dictionary with de `Full name` as a key and `3-letter-code` as a value.

[10]:
```
dic_states_original_correct=pd.Series(df_estado_iso['3-letter-code'].
 ↪values,index=df_estado_iso['Full name']).to_dict()
for state in states_full_name:
    magic_towns.
 ↪loc[magic_towns['estado']==state,'estado']=dic_states_original_correct[state]
magic_towns.head()
```

[10]:

	pueblo_magico	estado	pob_2010	pob_2015
0	Asientos	AGU	48358	50864
1	Calvillo	AGU	57627	60760
2	San José de Gracia	AGU	7160	9661
3	Tecate	BCN	89999	110870
4	La Paz	BCS	265717	293687

1.1.3 Analysis

In this section, we show a executive summary for the historical evolution of International tourism in Mexico.

Before to begin, we see the main info and check the differents cathegories of tourism.

[11]:
```
mexico_tourism['fecha'] = pd.to_datetime(mexico_tourism['fecha'],dayfirst=True)
mexico_tourism.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 71 entries, 0 to 70
Data columns (total 6 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   fecha                        71 non-null     datetime64[ns]
 1   visitantes_internacionales   71 non-null     int64
 2   turismo_al_interior          71 non-null     int64
 3   turismo_fronterizo           71 non-null     int64
 4   excursionistas _fronterizos  71 non-null     int64
 5   pasajeros_crucero            71 non-null     int64
dtypes: datetime64[ns](1), int64(5)
memory usage: 3.5 KB
```

We have four tourism cathegories:

1. turismo al interior
2. turismo fronterizo
3. excursionistas fronterizos
4. pasajeros crucero

From the dataset we obtain the information of what years and months we have information of international tourism.

[12]:
```
year_tourism=mexico_tourism['fecha'].dt.year
month_tourism=mexico_tourism['fecha'].dt.month
mexico_tourism['year']=year_tourism
mexico_tourism['month']=month_tourism
set_years_tourism=set(year_tourism)
set_months_tourism=set(month_tourism)
print(set_years_tourism)
print(set_months_tourism)
```

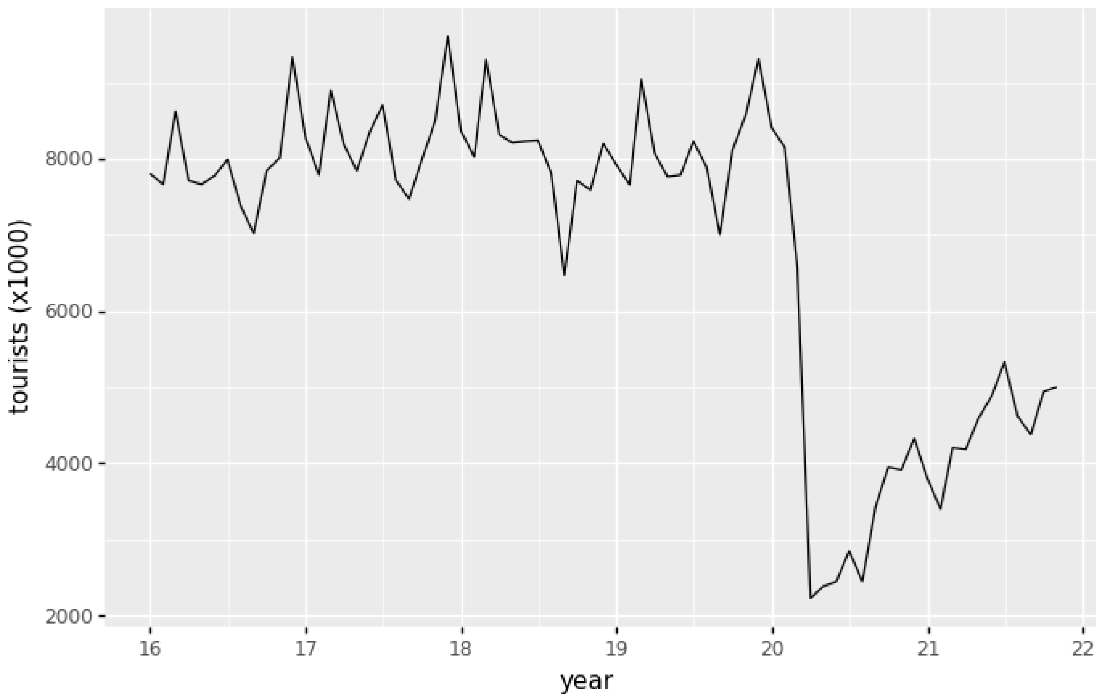
```
{2016, 2017, 2018, 2019, 2020, 2021}
{1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12}
```

[13]:
```
print('First day of registration ',mexico_tourism.iloc[0]['fecha'])
print('Last day of registration ',mexico_tourism.iloc[-1]['fecha'])
```

```
First day of registration  2016-01-01 00:00:00
Last day of registration  2021-11-01 00:00:00
```

First, we graph the evolution of total tourism from 01/01/2016 to 01/11/2021

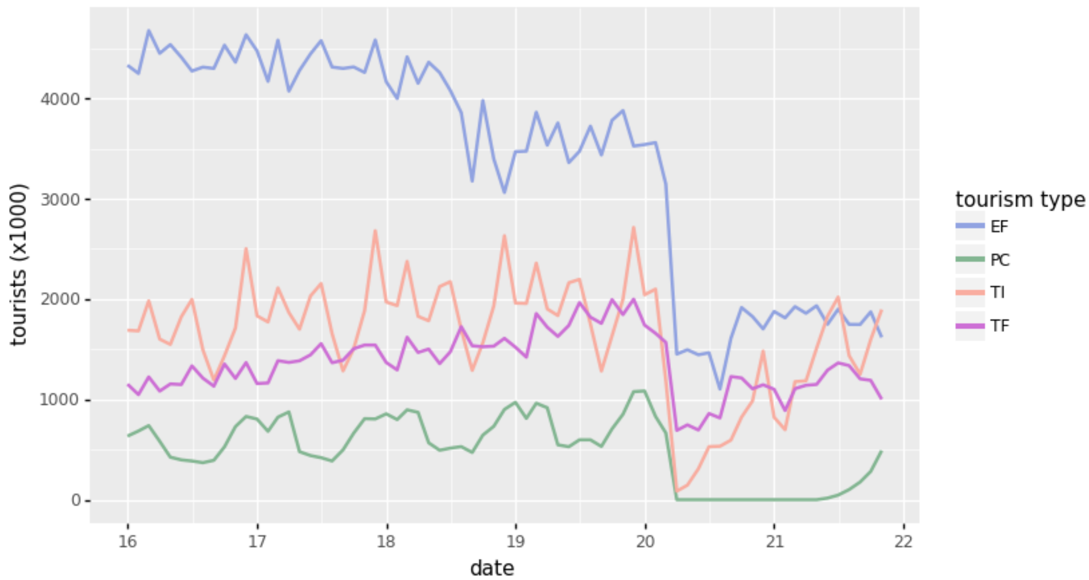
[14]:
```
from plotnine import *
gg1=ggplot(mexico_tourism)+geom_line(aes(x='fecha',y='visitantes_internacionales'))+theme(figur
 ↪(x1000)')+scale_x_date(date_breaks='1 year',date_labels='%y')
gg1
```



[14]:
```
<ggplot: (8754084237210)>
```

Afterwards, we graph the evolution of the international tourism per cathegory in all the time range we have.

[15]:
```
colors_palette=["#91A3E1", "#83B692","#F9ADA0", "#CD6FD5"]
tourism_cathegory=list(mexico_tourism.columns[2:6])
dfm_mexico_tourism = mexico_tourism.melt(id_vars=['year', 'fecha'],␣
 ↪value_vars=tourism_cathegory)
gg2=ggplot(dfm_mexico_tourism)+geom_line(aes(x='fecha',y='value',color='variable',group='variab
 ↪year',date_labels='%y')+theme(figure_size=(8,5))+labs(x='date', y='tourists␣
 ↪(x1000)')+scale_color_manual(values=colors_palette,name='tourism␣
 ↪type',labels=['EF','PC','TI','TF'])
gg2
```



[15]: <ggplot: (8754084144628)>

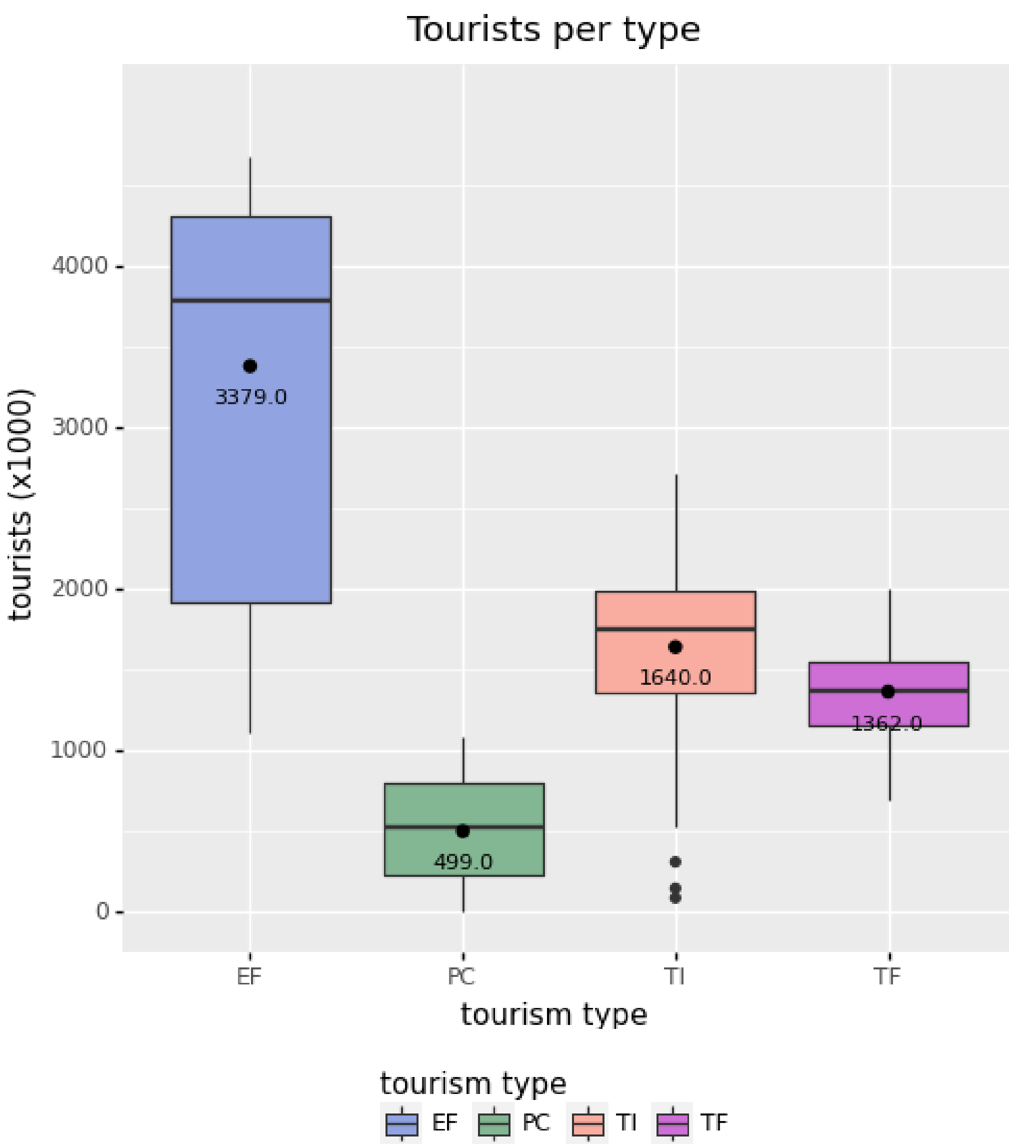
Where EF,PC,TI, and TF correspond to *excursionistas fronterizos,pasajeros en crucero,turismo al interior*, and *turismo fronterizo* respectively.

We see the evolution of the tourism from 2016 to 2021. Clearly, at the beginning of 2020 we observe an abrupt decreasing of the four tourism cathegories. It could be for the COVID-19 pandemic. Moreover, we observe a in different proportion each cathegory after 2020. Before 2020 we observed in decreasing order of proportion EF, TI, TF, and PC.

We continue to evaluate the distribution of each tourism cathegory. We are going to see this with a boxplot.

[16]:
```
import numpy as np
def mean(x):
    return np.mean(x)
means=pd.DataFrame(mexico_tourism[tourism_cathegory].mean())
#mexico_tourism.boxplot(column=tourism_cathegory,figsize=(10,7),showmeans=True)
gg3=ggplot(dfm_mexico_tourism)+geom_boxplot(aes('variable','value'))+labs(x='tourism␣
 ↪type',y='tourists (x1000)')
gg3= (
    ggplot(dfm_mexico_tourism, aes(x="variable", y="value"))
    + geom_boxplot(aes(fill="variable"))
    + xlab("tourism type")
    + ylab("tourists (x1000)")
    + scale_y_continuous(breaks=np.arange(0, 5000, 1000),
                         limits=[0, 5000])
    + scale_x_discrete(labels=['EF','PC','TI','TF'])
    + ggtitle("Tourists per type")
```

```
    + theme(figure_size=(6,6),legend_position="bottom",legend_box_spacing=0.4)
    + stat_summary(fun_y= mean, geom="point", colour="black", size=2,
                position = position_dodge2(width = 0.75))
    +guides(fill=guide_legend(title="tourism type"))
    +scale_fill_manual(values=colors_palette,labels=['EF','PC','TI','TF'])
    +annotate(geom='text',x=1,y=np.floor(means.loc['excursionistas␣
↪_fronterizos'][0])-200,label=np.floor(means.loc['excursionistas␣
↪_fronterizos'][0]),size = 8)
    +annotate(geom='text',x=2,y=np.floor(means.
↪loc['pasajeros_crucero'][0])-200,label=np.floor(means.
↪loc['pasajeros_crucero'][0]),size = 8)
    +annotate(geom='text',x=3,y=np.floor(means.
↪loc['turismo_al_interior'][0])-200,label=np.floor(means.
↪loc['turismo_al_interior'][0]),size = 8)
    +annotate(geom='text',x=4,y=np.floor(means.
↪loc['turismo_fronterizo'][0])-200,label=np.floor(means.
↪loc['turismo_fronterizo'][0]),size = 8)
)
gg3
```



[16]: <ggplot: (8754054257255)>

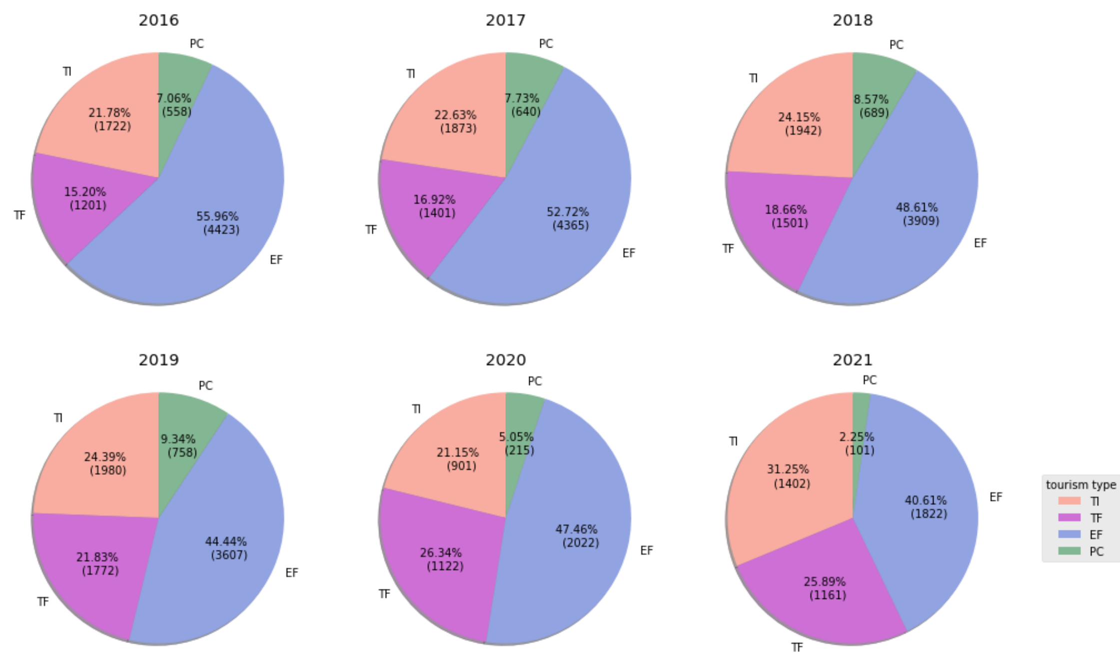
The last plot show outliers in `turismo_al_interior` and asymmetry in `excursionistas_fronterizos`. That could be explain for the bigger drop in 2020 of this cathegories in a short period of time with respect to the others. In addition, we observe a high variability in the cathegory of `excursionistas_fronterizos`, therefore we can draw from the data that this tourism type changed more from 2016 to 2021. Moreover, we show in number the mean of each cathegory during that period.

Finally, we are going to show the mean proportion of each tourism cathegory per year.

[17]:

```python
# Import libraries
from matplotlib import pyplot as plt
plt.style.use('ggplot')
fig,axs= plt.subplots(2,3,figsize=(15,15))
list_of_years=list(set_years_tourism)
dic_tourism_cathegory={
'excursionistas _fronterizos':'EF',
'pasajeros_crucero':'PC',
'turismo_al_interior':'TI',
'turismo_fronterizo':'TF'
}
dic_colors_cathegory={
'excursionistas _fronterizos':colors_palette[0],
'pasajeros_crucero':colors_palette[1],
'turismo_al_interior':colors_palette[2],
'turismo_fronterizo':colors_palette[3]
}
index_year=0
def make_autopct(values):
    def my_autopct(pct):
        total = sum(values)
        val = int(round(pct*total/100.0))
        return '{p:.2f}% \n ({v:d})'.format(p=pct,v=val)
    return my_autopct
for i in range(2):
    for j in range(3):
        df_aux=mexico_tourism[mexico_tourism['year']==list_of_years[index_year]]
        total_tourists=df_aux['visitantes_internacionales'].to_numpy()
        mean_total_tourists=np.mean(total_tourists)
        df_aux=df_aux[tourism_cathegory]
        cathegory_mean=pd.DataFrame(df_aux.mean())
        pie_labels=[dic_tourism_cathegory[c] for c in cathegory_mean.index.
 ↪to_list()]
        pie_colors=[dic_colors_cathegory[c] for c in cathegory_mean.index.
 ↪to_list()]
        wedges, texts, autotexts=axs[i,j].pie(cathegory_mean[0].to_numpy(),
        autopct = make_autopct(cathegory_mean[0].to_numpy()),
        shadow = True,
        labels=pie_labels,
        colors=pie_colors,
        startangle = 90,
        textprops=dict(color='k', fontsize=10),
        radius=1.2
        )
        axs[i,j].set_title(list_of_years[index_year],pad=20)
        index_year+=1
# Adding legend
```

```
axs[i,j].legend(wedges, pie_labels,
    title ="tourism type",
    loc ="center left",
    bbox_to_anchor =(1.2, 0, 0.6, 1))
plt.subplots_adjust(left=0.1,
                    bottom=0.2,
                    right=0.9,
                    top=0.7,
                    wspace=0.3,
                    hspace=0.3)
```



In this plot, we show the mean proportion of each tourism cathegory per year. We observe an increasing behavior of `turismo al interior` with respect to the mean of each year. Analogously, we observe that in `turismo fronterizo`, with the only exception of 2020 where every cathegory dropped. On the other hand, we observe an decreasing behavior from 2016 to 2022 of `pasajeros crucero` and `excursionistas fronterizos`.

We have already seen that each cathegory drop from 2019 to 2020. Computing the relative drop from 2019 to 2020 of each cathegory we obtain that `pasajeros crucero` dropped to 28% of tourists with respect to 2019,`turismo al interior` dropped to 45%, `excursionistas fronterizos` dropped to 59%, and `turismo fronterizo` dropped to 63% with respect to 2019's data. We can conclude that `pasajeros crucero` was the cathegory with the higher drop with respect to the mean in 2020.

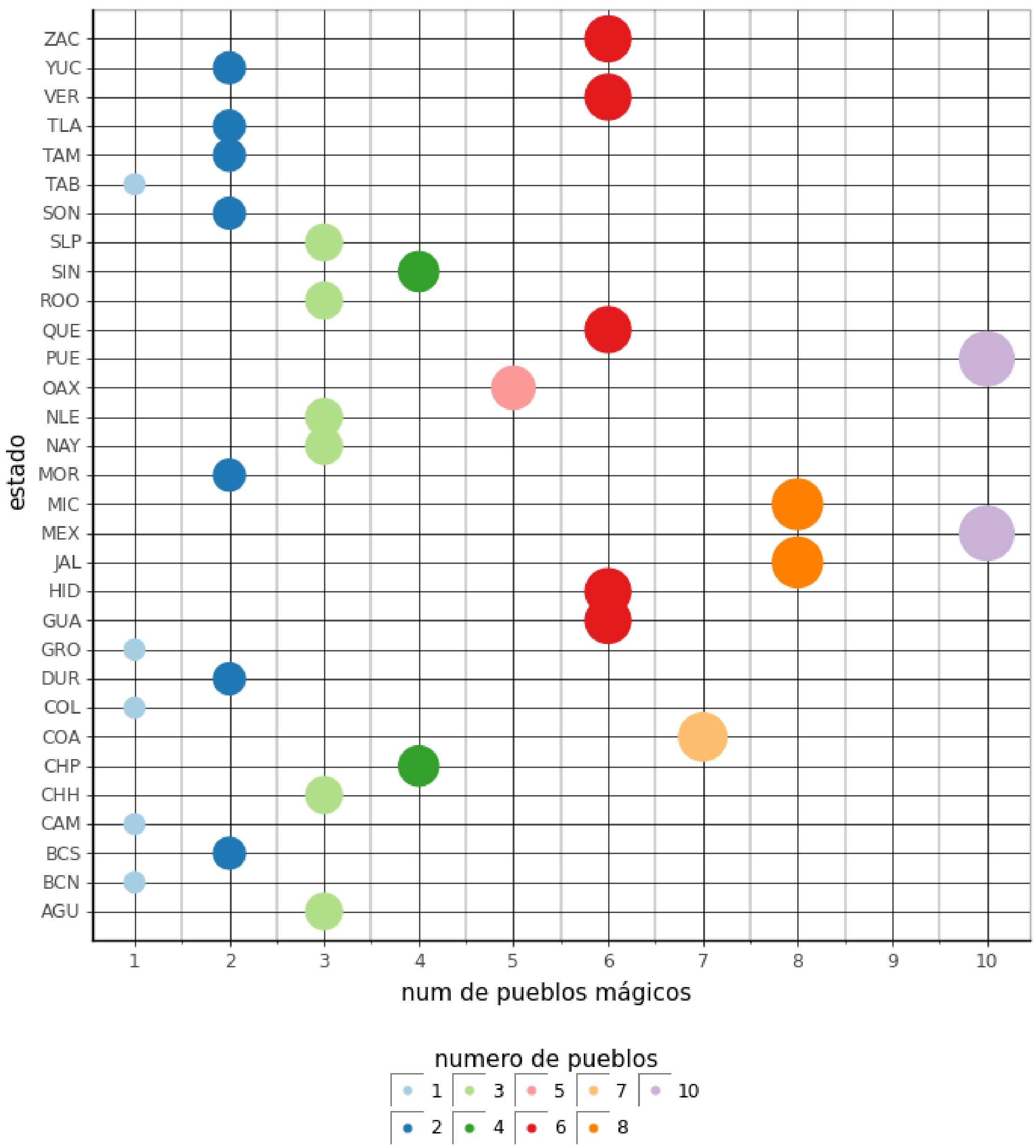
1.1.4 Creativity to communicate analytical results

Finally, we will answer The Leadership team's question: *The number of Pueblos mágicos in each state*

It is an interesting question know if there are states that do not have *Pueblos mágicos*, therefore a barplot is natural option for that task because we can see and contrast the number of *Pueblos mágicos* of each Mexico state. However, in this plot we have 32 states and it could be difficult to see the exact number of *Pueblos mágicos* and how many states have the same number of *Pueblos mágicos*.

In the following code cell we will show the plot that tries to solve those problems and with the information required by The Leadership team.

[18]:
```
dic_num_magic_towns_per_state={}
estado_iso_code=df_estado_iso['3-letter-code'].to_list()
for state in estado_iso_code:
    df_aux=magic_towns[magic_towns['estado']==state]
    dic_num_magic_towns_per_state[state]=df_aux.shape[0]
df_num_magic_towns_per_state=pd.DataFrame({'estado':
 ↪dic_num_magic_towns_per_state.keys(),'num_pueblos_magicos':
 ↪dic_num_magic_towns_per_state.values()})
gg5=(
    ggplot(df_num_magic_towns_per_state,aes(x='estado',y='num_pueblos_magicos'))
  ␣
 ↪+geom_point(aes(size='num_pueblos_magicos',color='factor(num_pueblos_magicos)'))
    +scale_size_continuous(guide=False,range=(5,14))
    +scale_color_brewer(type='qual',palette=3,name='numero de pueblos')
    +scale_x_discrete(expand=(0, 1))
    +labs(x='estado',y='num de pueblos mágicos')
    +scale_y_continuous(breaks=np.arange(1,11,1))
    +coord_flip()
    +theme_light()
    +theme(figure_size=(8,8),legend_position="bottom",legend_box_spacing=0.
 ↪5,line=element_line(color='black'),
    legend_title_align='center')
)
gg5
```



[18]: <ggplot: (8754084162482)>

The last graphs in x-axis has the number of *Pueblos mágicos* and in y-axis the states of Mexico. For each row or state we have a dot with center aligned with the exact number *Pueblos mágicos* in that state, therefore we answer the main question. In addition, we can observe that points with the same color correspond to states with the same number of *Pueblos mágicos* and the legend says what is the number of *Pueblos mágicos* these states have. Moreover, the size of the dots increase with the number of *Pueblos mágicos* that represent. The increasing size helps to identify how many states have the maximum and minimun number of *Pueblos mágicos*, then you can identify what are these states.

1.2 Machine Learning solutions mindset

The **Business use case** we chose is **Case 1**. We propose a solution for accepting credit card customers in a digital bank.

1.2.1 Step 1

First of all, we think in the database which help us to make a decision.

In general, credit card decisions are made based in the credit history. The credit history we will use is the *Buró de crédito*'s history.

Buró de crédito's credit history for each person contain a list in detail of past credits requested to other credit institutions and the status of each of this credits.

There are 3 status in *Buró de crédito* system, they are: 1. up to date with payment. 2. From 1 to 89 delay days. 3. More than 90 delay days.

Of course, the status depends on the type of credit, amount to pay, credit limit, maximum credit, current balance and customer's current income, etc.

We only have in mind the maximum credit, current balance, and the status of all credits in the history because we are in a digital bank context. That information could help to measure the payment ability of the customer.

In *Buró de crédito* we can find that input (maximum credit,current balance) with its respect status.

With that information the idea is training a Neural Network for binary classification problem. The classes are *up to date with payment* and the other one is if the status is *From 1 to 89 delay days* or *More than 90 delay days*

The decision could be based in the output of this Neural Network given a credit maximum and a fixed current balance.

1.2.2 Step 2

In this part, we are going to state the last approach mathematically.

First of all, we need to abstract the data in mathematical notation.

The sample of a customer, obtaining in a Query to *Buró de crédito*'s database, is of the form

$$\{(X_{1i}, X_{2i}, Y_i) \in \mathbb{R}^2 \mid Y_n \in \{0,1\}, i = 1,2,\ldots,n\},$$

where n is the number of credits.

Here 1. X_{1i} is the maximum credit of i-th credit. 2. X_{2i} is the current balance of i-th credit. 3. Y_i is a dummy variable such as

$$Y_i = \begin{cases} 1 & \text{if } i\text{-th credit has } \textit{up to date payment} \text{ status} \\ 0 & \text{otherwise} \end{cases}$$

Determine the number of hidden layers and the number of neurons of each layer is something that requires experimentation but it is task that can be done with a framework.

Because of our approach our neural network has two neurons in the input layer and one in the output layer.

We can use sigmoid activation function its form is

$$\sigma(x) = \frac{1}{1+e^{-x}},$$

and its range is $[0,1]$. Therefore our Neural Network is a function $f : \mathbb{R}^2 \to [0,1]$.

For an input $(\hat{X}_1, \hat{X}_2)$ we set the correspondent dummy variable as

$$\hat{Y} = \begin{cases} 1 & \text{if } f(\hat{X}_1, \hat{X}_2) > 0.5 \\ 0 & \text{otherwise} \end{cases}$$

Thinking in a extreme case, if we want to accept credit card customer we train the neural network with his personal dataset, then we test with his required credit and a 0 or fixed tolerable current balance. We accept the customer if we obtain a 1 in the last classification and we do not accept him if we obtain a 0.

On the other hand, if we do not have enough data for the customer we can fixed a credit based in his current income but it needs to be an amount with a low risk for the company.

1.2.3 Step 3

We need to identify the main computation tasks in this solution. The first one is to obtain the personal data set of each customer from *Buró de Crédito*. The second one is the computational cost for training the neural network in order to make a decision on the customer request.

For the first task we need to get information from the customer and with that information obtain the customer's sample stated in the last section.

If we already have the customer's personal data, then we can ask for the sample required for the neural network training through *BigQuery* by Google Cloud. This technology has support for connections to a external database source. In addition, it allows to execute statistics of large amount data in real-time that is exactly what we need in a digital bank.

For the Machine Learning task, I mean, the Neural Network training, we can use *Vertex AI* by Google Cloud. This technology supports AutoML that is a useful tool for training different Neural Networks corresponding to each customer, and we avoid the hard task of checking the hidden structure of the Neural Network. In addition,we can assess the final model in a friendly way. Finally, we deploy the model for online predictions required in our digital bank.