



COMPLEX DECISIONS SIMPLIFIED

# Data Visualisation in Python

Quick and easy routes to plotting magic

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# Outline

- Data Visualisation Basics
- Basic Python Setup & Core Libraries
- Code examples and comparisons
- What to avoid



# EdgeTier

EdgeTier specialise in data and artificial intelligence products for customer contact centres.



Commercially focused SaaS to increase revenue and reduce costs


Focus on data science, machine learning, and automation



AI system works alongside customer service agents to increase efficiency by 100%



# Data Visualisation



Data visualisation is a general term that describes any effort to help people understand the significance of **data** by placing it in a visual context.





# Data Visualisation

**Choice of Data Visualisation Tool is important**

Iteration speed

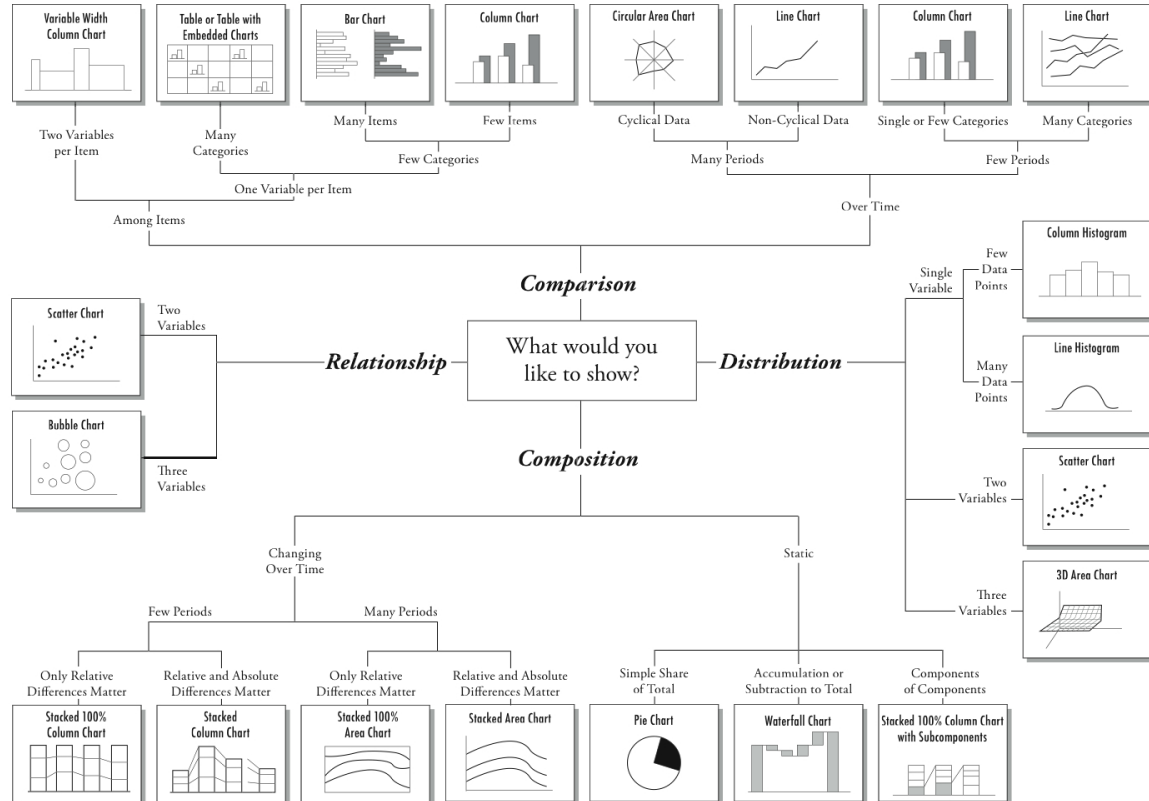
Un-intrusive

Flexible

Aesthetically pleasing



# Chart Choice





# Chart Choice – Fearsome Foursome



## **BARPLOT**

Represents the value of entities using bar of various length.



## **HISTOGRAM**

An accurate graphical representation of the distribution of numeric data.



## **SCATTER PLOT**

Show the relationship between 2 numeric variables.



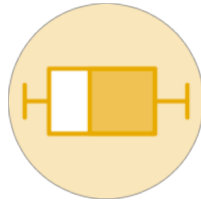
## **LINE CHART**

Shows the evolution of numeric variables.



# Chart Choice – Fearsome Foursome

## Special Mentions



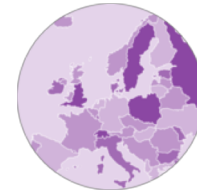
### **BOXPLOT**

Summarize the distribution of numeric variables



### **SANKEY DIAGRAM**

Showing flows with smooth links



### **CHOROPLETH MAP**

Display an aggregated value for each region of a map



# Data Visualisation in Python



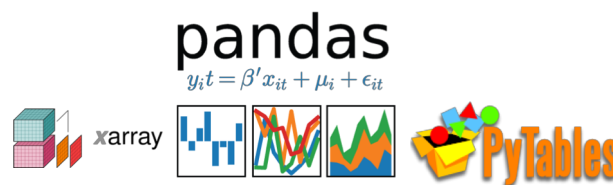
## Python Visualisation

- Lots of choice of libraries
- Many tools, with varied APIs & outputs
- Best to conquer and become familiar with one / two

Interactive environment



Data Manipulation Library



Visualisation Library







# Matplotlib

**matplotlib**

## Grand daddy of Python Plotting

Low level plotting library with  
Matlab-like API

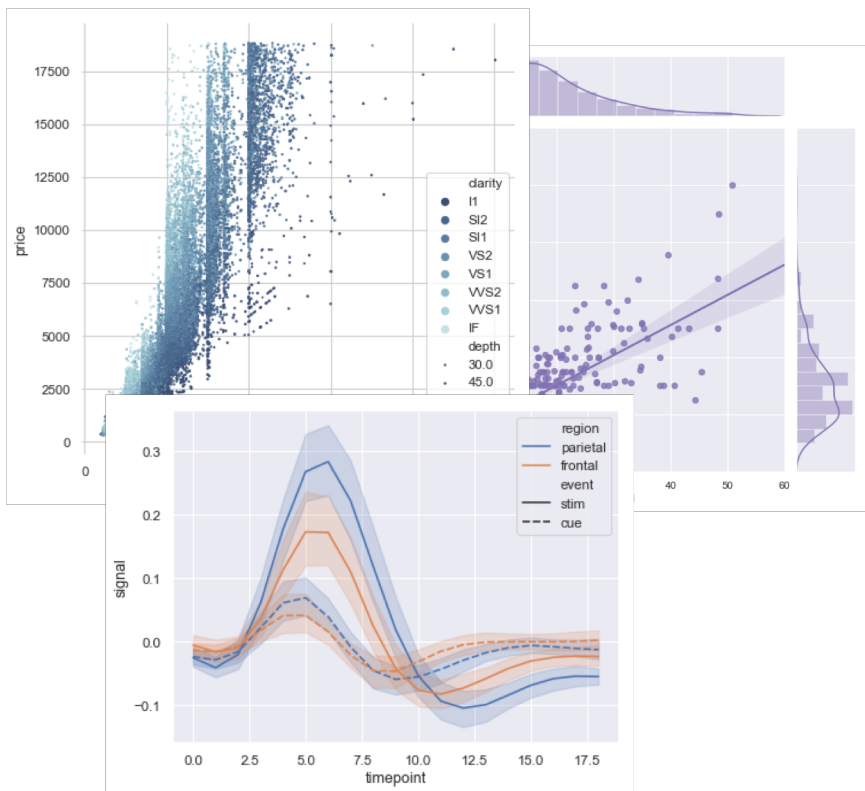
- + Very flexible, complete control
- Verbose plots, aesthetically lacking,  
sometimes difficult with Pandas

...need to know enough to debug...





# Pandas / Seaborn / Altair



## Higher level plotting

**Pandas** – Visualisation API built into DataFrame & Series objects, interface to Matplotlib.

**Seaborn** – extends and provides high-level API on Matplotlib with improved styling.

**Altair** – Built on “Vega-Lite” visualisation grammar. Allows some interactive plots in Jupyter Notebooks.



# Basic Notebook Setup



## Imports on Matplotlib

Top of notebook – inline  
vs notebook style.

Theme also can be  
chosen here

```
# Pandas used for data analysis and managemment
import pandas as pd
# Numpy library for arry and numerical functions
import numpy as np
# Matplotlib pyplot provides plotting API
import matplotlib as mpl
from matplotlib import pyplot as plt
# "Standard" to load seaborn as "sns"
import seaborn as sns
# Altair is a visualisation library based on Vega
import altair as alt
alt.renderers.enable('notebook')

# For output plots inline in notebook:
%matplotlib inline
# For interactive plot controls on Matplotlib output:
# %matplotlib notebook

# Set the default figure size for all inline plots
# (note: needs to be AFTER the %matplotlib magic)
plt.rcParams['figure.figsize'] = [8, 5]
```



# Sample Data



EdgeTier relevant sample dataset on chat system performance. Agents answering customer chats from different websites and languages – 5477 chats over 100 agents.

```
In [7]: data.head()
```

```
Out[7]:
```

	user_id	chat_id	language	number_messages	handling_time	start_time	website	website_summary
0	User 1495	8347	English	7	187.0	2018-05-30 11:59:48.422292	Website B	Website B
1	User 1495	8348	English	7	258.0	2018-05-30 11:25:15.111164	Website B	Website B
2	User 1495	8349	English	8	529.0	2018-05-30 10:40:38.255353	Website B	Website B
3	User 1495	8350	English	14	840.0	2018-05-30 12:08:16.612382	Website B	Website B
4	User 1495	8351	English	11	1283.0	2018-05-30 11:15:28.393306	Website B	Website B



# The Bar Plot







# The Bar Plot - Matplotlib

## Bar plot of chats per user

```
In [64]: chats_per_user = data.groupby('user_id')['chat_id'].count().reset_index()
chats_per_user.columns = ['user_id', 'number_chats']
chats_per_user = chats_per_user.sort_values('number_chats', ascending=False)
chats_per_user.head()
```

Out[64]:

	user_id	number_chats
49	User 1395	406
1	User 1251	311
78	User 1495	283
79	User 1497	276
39	User 1358	236

Python visualisation libraries often require that the data for plotting is pre-formatted for visualisation.

For Pandas and Matplotlib, the visualisation library often only present the values, and does not do calculations.



# The Bar Plot - Matplotlib

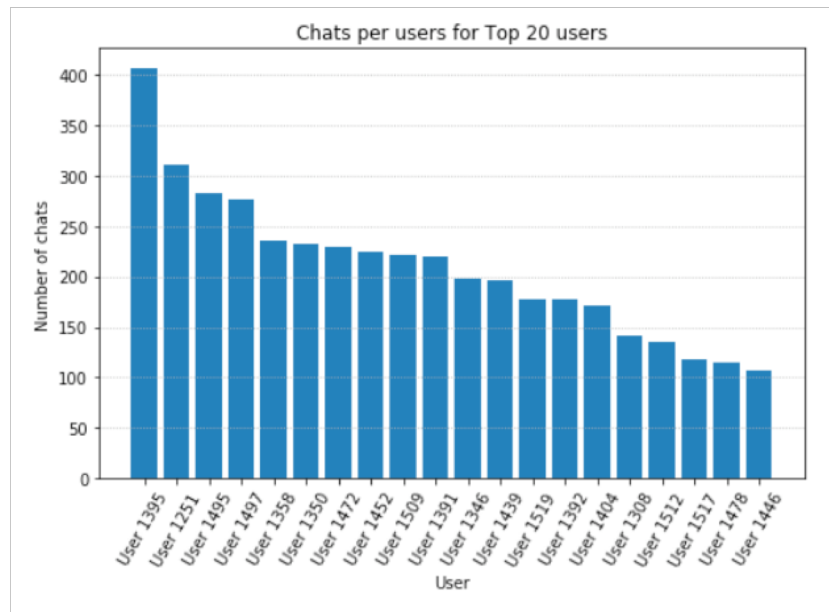


matplotlib

```
top_n = 20
plt.bar(x=range(top_n),
        height=chats_per_user[0:top_n]['number_chats'])
plt.xticks(range(top_n), chats_per_user[0:top_n]['user_id'],
           rotation=60)
plt.ylabel("Number of chats")
plt.xlabel("User")
plt.title("Chats per users for Top 20 users")
ax = plt.gca()
ax.yaxis.grid(linestyle=':')
```

.bar() function does the work, manually position 'x' labels and positions.

Most code here is formatting and display.



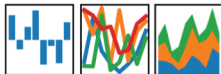


# The Bar Plot - Pandas



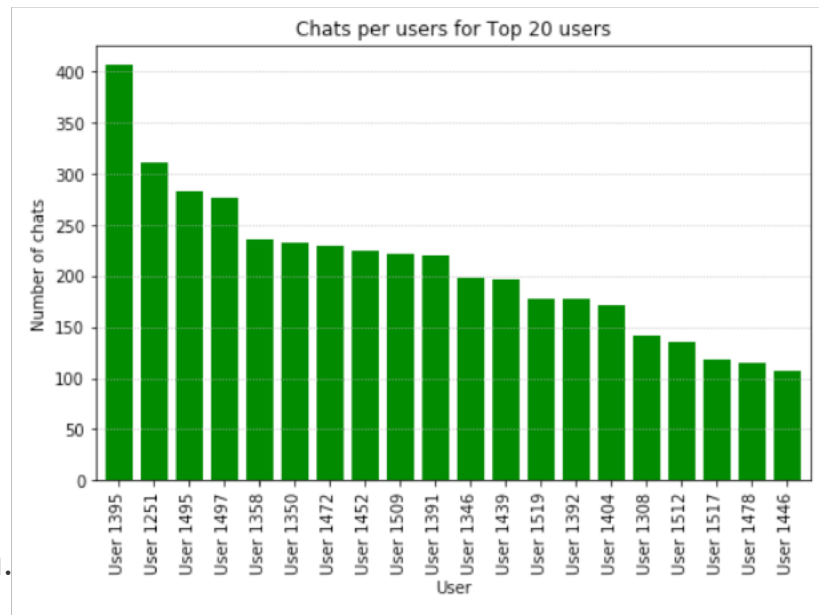
pandas

$$y_i t = \beta' x_{it} + \mu_i + \epsilon_{it}$$



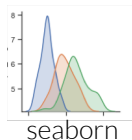
```
chats_per_user[0:20].plot(  
    x='user_id', y='number_chats',  
    kind='bar', legend=False, color='green',  
    width=0.8  
)  
plt.ylabel("Number of chats")  
plt.xlabel("User")  
plt.title("Chats per users for Top 20 users")  
plt.gca().yaxis.grid(linestyle=':')
```

Plot output is Matplotlib – same manipulation.  
Slightly simpler API / data access.





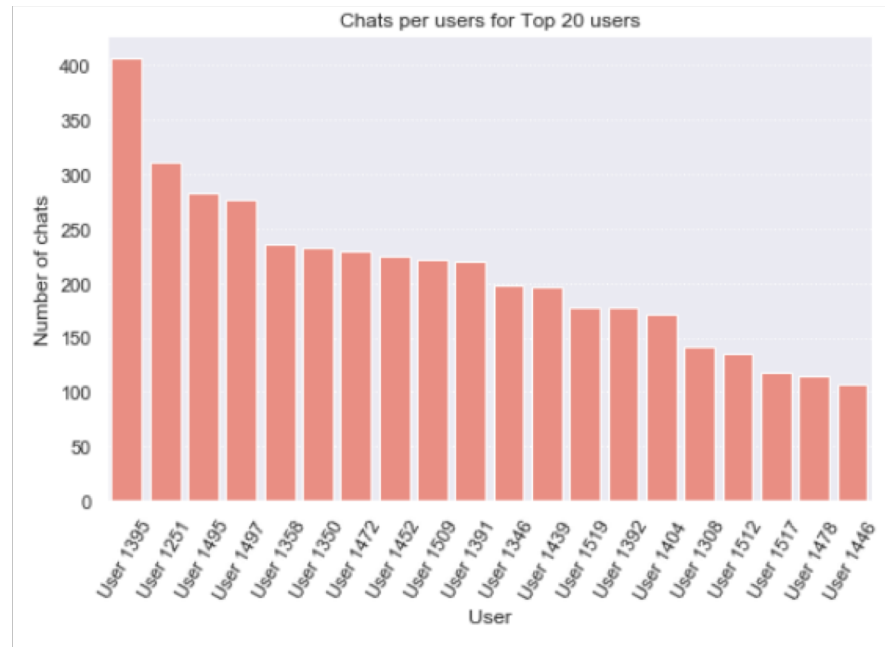
# The Bar Plot - Seaborn



```
sns.barplot(x='user_id', y='number_chats',  
            color='salmon', data=chats_per_user[0:20])  
plt.xticks(rotation=60)  
plt.ylabel("Number of chats")  
plt.xlabel("User")  
plt.title("Chats per users for Top 20 users")  
plt.gca().yaxis.grid(linestyle=':')
```

Simpler data access again.

Same Matplotlib formatting functions





# The Bar Plot - Altair

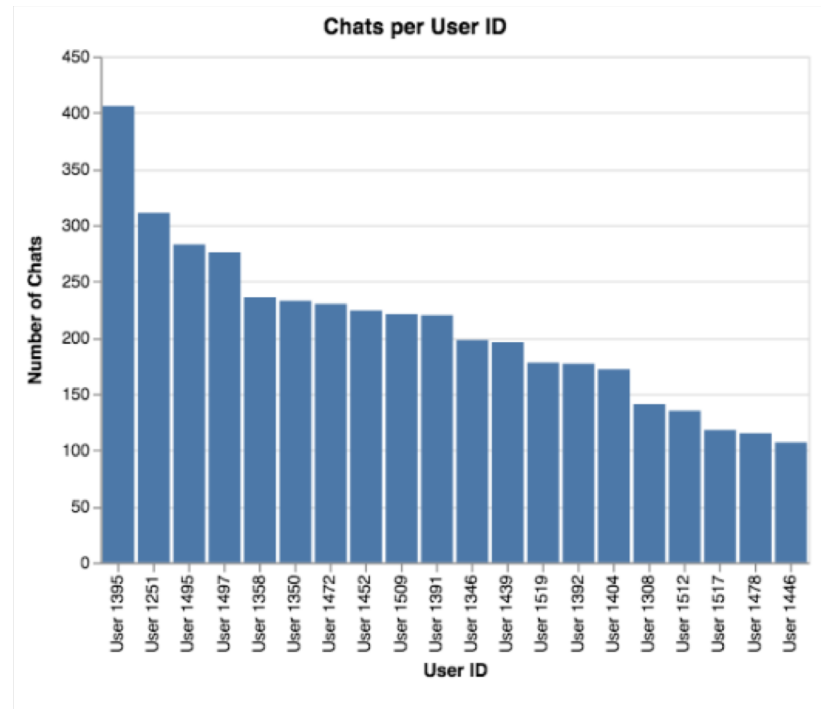


```
bars = alt.Chart(  
  chats_per_user[0:20], title='Chats per User ID').mark_bar().encode(  
  x=alt.X(  
    'user_id',  
    sort=alt.EncodingSortField(field='number_chats',  
                               op='sum',  
                               order='descending'),  
    axis=alt.Axis(title='User ID')),  
  y=alt.Y(  
    'number_chats',  
    axis=alt.Axis(title='Number of Chats'))  
  )  
bars
```

Not Matplotlib-based – very different syntax and formatting.

Ordering was difficult here.

Only one command for everything. JSON format behind.





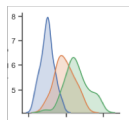




# The Bar Plot

## matplotlib

```
top_n = 20
plt.bar(x=range(top_n),
        height=chats_per_user[0:top_n]['number_chats'])
plt.xticks(range(top_n), chats_per_user[0:top_n]['user_id'],
           rotation=60)
plt.ylabel("Number of chats")
plt.xlabel("User")
plt.title("Chats per users for Top 20 users")
ax = plt.gca()
ax.yaxis.grid(linestyle=':')
```

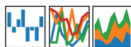


seaborn

```
sns.barplot(x='user_id', y='number_chats',
            color='salmon', data=chats_per_user[0:20])
plt.xticks(rotation=60)
plt.ylabel("Number of chats")
plt.xlabel("User")
plt.title("Chats per users for Top 20 users")
plt.gca().yaxis.grid(linestyle=':')
```

## pandas

$$y_t = \beta'x_t + \mu_i + \epsilon_u$$



```
chats_per_user[0:20].plot(
    x='user_id', y='number_chats',
    kind='bar', legend=False, color='green',
    width=0.8
)
plt.ylabel("Number of chats")
plt.xlabel("User")
plt.title("Chats per users for Top 20 users")
plt.gca().yaxis.grid(linestyle=':')
```



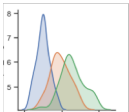
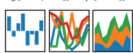
```
bars = alt.Chart(
    chats_per_user[0:20], title='Chats per User ID').mark_bar().encode(
    x=alt.X(
        'user_id',
        sort=alt.EncodingSortField(field='number_chats',
                                   op='sum',
                                   order='descending'),
        axis=alt.Axis(title='User ID')),
    y=alt.Y(
        'number_chats',
        axis=alt.Axis(title='Number of Chats')
    )
)
```



# Prettier Pandas Plots

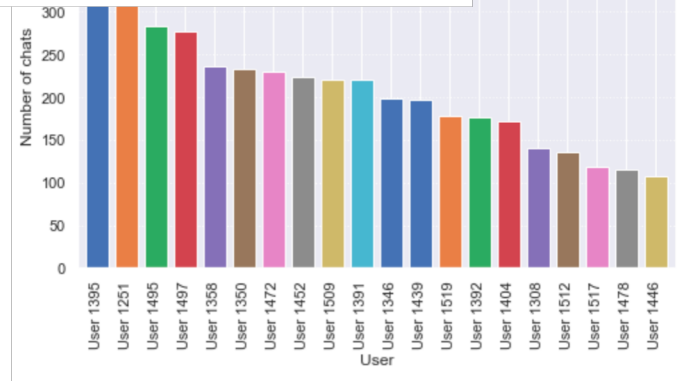
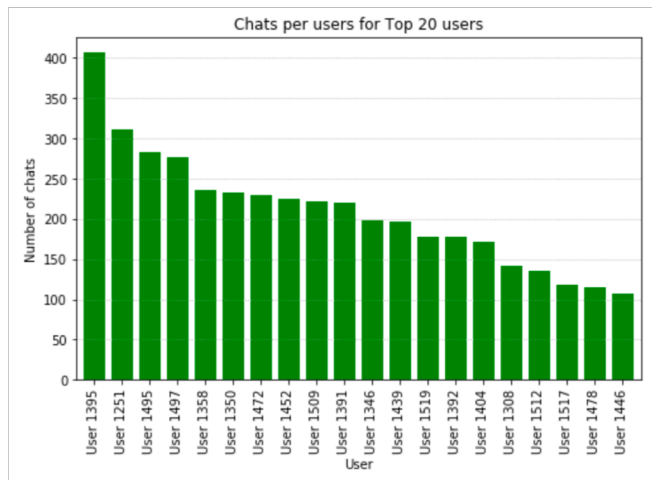
pandas

$$y_{it} = \beta'x_{it} + \mu_i + \epsilon_{it}$$



seaborn

```
import seaborn
sns.set()
chats_per_user[0:20].plot(
    x='user_id', y='number_chats',
    kind='bar', legend=False,
    width=0.8
)
plt.ylabel("Number of chats")
plt.xlabel("User")
plt.title("Chats per users for Top 20 users")
plt.gca().yaxis.grid(linestyle=':')
```



Seaborn styles are applied to all matplotlib plots –  
Cheat your way to nicer looking Pandas Plots!



# More Challenging Bar Plot

For the top 20 agents, what was the split of the top websites?

We want a 'stacked bar' for this visualisation.

```
# Only include the top 5 Websites
chats_per_user = data.groupby(
    ['user_id', 'website_summary']
)['chat_id'].count().reset_index()
chats_per_user.columns = ['user_id', 'website', 'number_chats']

# Only include the top 20 chatters again
chats_per_user = \
    chats_per_user[chats_per_user['user_id'].isin(
        data['user_id'].value_counts().index[0:20].tolist()
    )]

# Sort the data with agents with most chats first
# First get the total chats:
temp = chats_per_user.\
    groupby('user_id')['number_chats'].\
    sum().\
    reset_index().\
    sort_values('number_chats', ascending=False)
temp.columns=['user_id', 'total_chats']
# Now merge these sums back onto the original data
chats_per_user = pd.merge(
    chats_per_user, temp, on='user_id'
).sort_values('total_chats', ascending=False)
```

	user_id	website	number_chats	total_chats
35	User 1395	Other	28	406
36	User 1395	Website A	114	406
37	User 1395	Website B	96	406
38	User 1395	Website C	102	406
39	User 1395	Website D	66	406

```
chats_per_user.shape
```

```
(100, 4)
```

```
chats_per_user['website'].value_counts()
```

```
Website A    20
Website B    20
Website C    20
Other         20
Website D    20
Name: website, dtype: int64
```

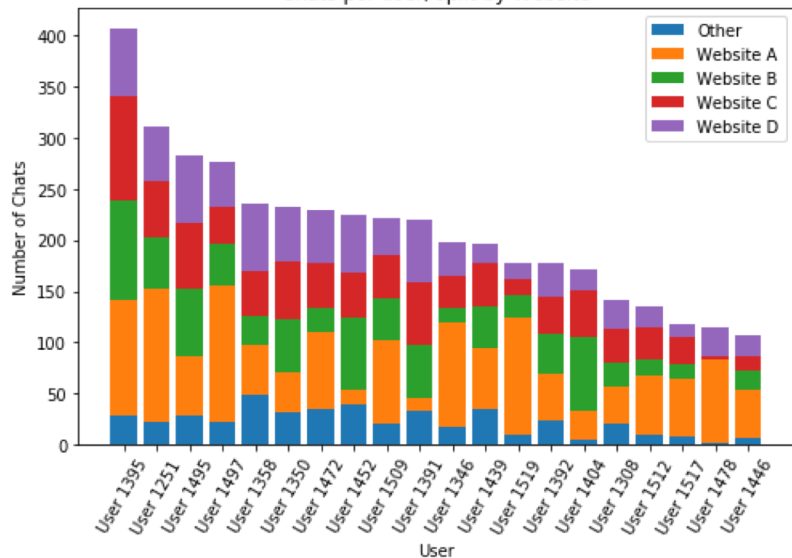


# Stacked Bar - Matplotlib



matplotlib

Chats per user, split by Website





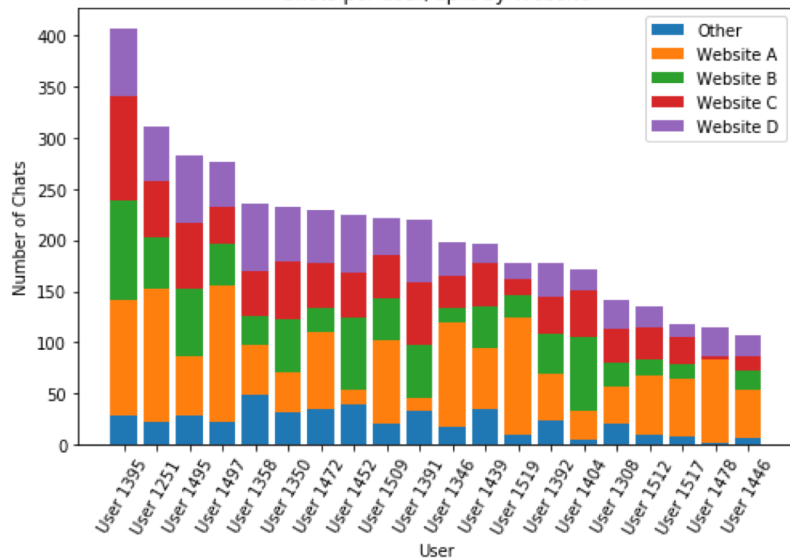


# Stacked Bar - Matplotlib



matplotlib

Chats per user, split by Website



```
x_position = list(range(20))
# For matplotlib, we manually track where bars start/finish
bars_bottom = np.zeros(20)

for website_string in chats_per_user['website'].unique():
    # Draw a set of bars for this website
    bar_height = chats_per_user[
        chats_per_user['website'] == website_string]['number_chats']
    plt.bar(
        x=x_position,
        height=bar_height,
        bottom=bars_bottom
    )
    # Remember where the bottom of these bars are
    bars_bottom = bars_bottom + bar_height.values

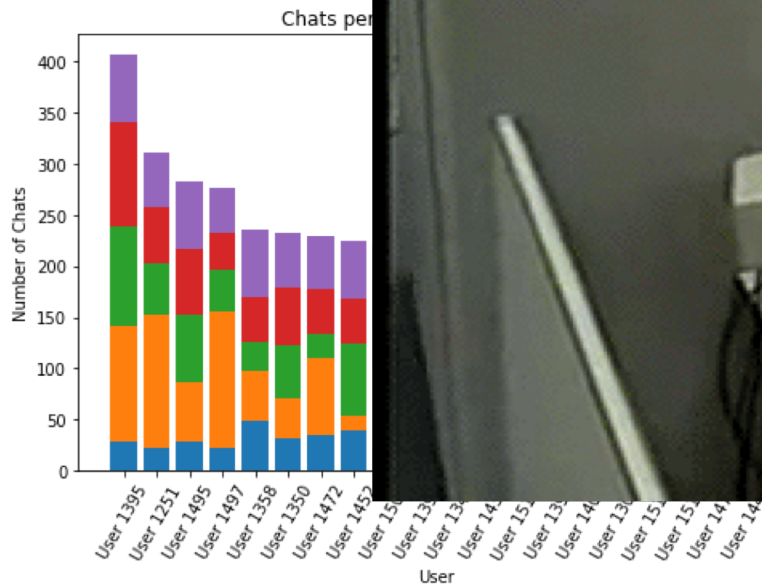
# Unique preserves order - so it's safe here.
plt.xticks(x_position, chats_per_user.user_id.unique(), rotation=60)
plt.xlabel('User')
plt.ylabel('Number of Chats')
plt.title('Chats per user, split by Website')
plt.legend(chats_per_user['website'].unique())
```



# Stacked Bar - Matplotlib



matplotlib



```
x_position = list(range(20))
```

```
start/finish
```

```
unique():
```

```
g]['number_chats']
```

```
ie(), rotation=60)
```

```
plt.legend(chats_per_user['website'].unique())
```

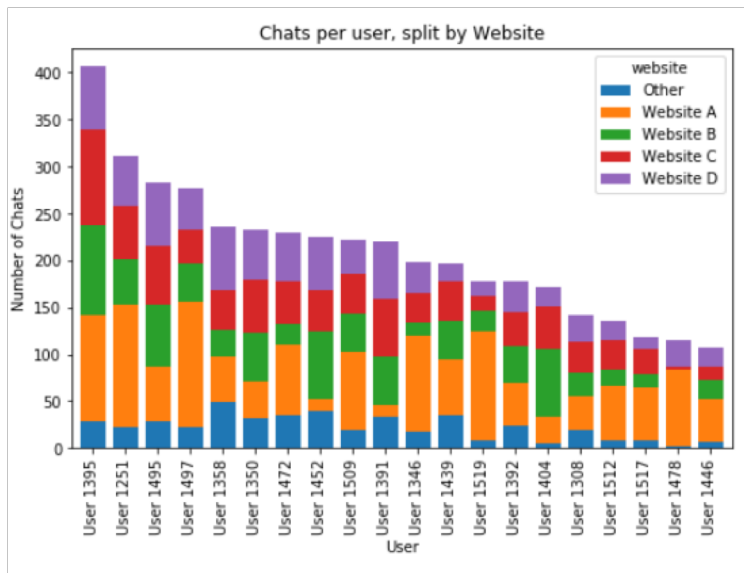
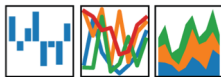


# Stacked Bar - Pandas



pandas

$$y_{it} = \beta' x_{it} + \mu_i + \epsilon_{it}$$



```
# Stacked bar in Pandas requires a data transformation
```

```
plot_data = chats_per_user.pivot(index='user_id',  
                                  columns='website',  
                                  values='number_chats')
```

```
# Wide format - sort by total chats by user.
```

```
plot_data = plot_data.iloc[plot_data.sum(axis=1).argsort()[::-1], :]  
plot_data.head()
```

	user_id	website	number_chats	total_chats
35	User 1395	Other	28	406
36	User 1395	Website A	114	406
37	User 1395	Website B	96	406
38	User 1395	Website C	102	406
39	User 1395	Website D	66	406



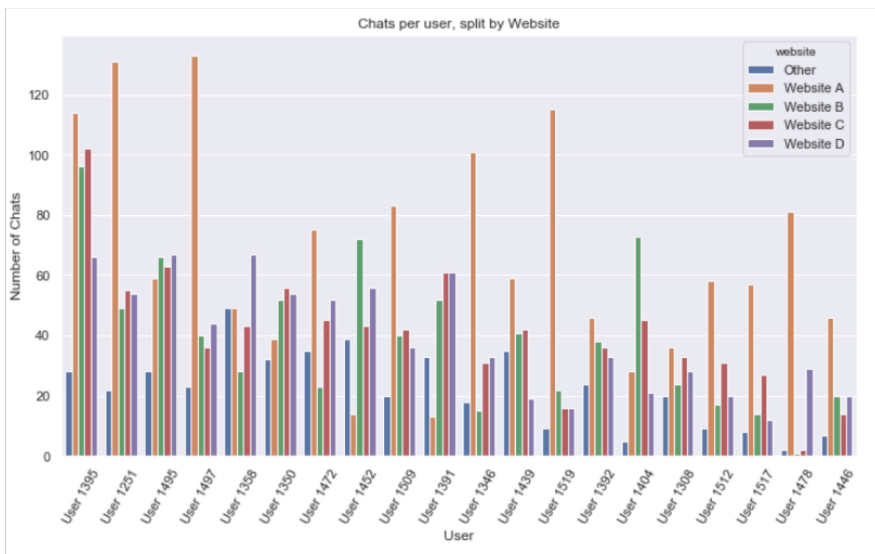
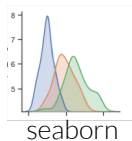
	website	Other	Website A	Website B	Website C	Website D
user_id						
User 1395		28	114	96	102	66
User 1251		22	131	49	55	54
User 1495		28	59	66	63	67
User 1497		23	133	40	36	44
User 1358		49	49	28	43	67

```
plot_data.plot(kind='bar', stacked=True, width=0.8)  
plt.xlabel('User')  
plt.ylabel('Number of Chats')  
plt.title('Chats per user, split by Website')
```

Plotting code is simple, but data manipulation required.



# Stacked Bar - Seaborn



```
sns.set()
sns.barplot(x='user_id',
            y='number_chats',
            hue='website',
            data=chats_per_user)

plt.xlabel('User')
plt.ylabel('Number of Chats')
plt.title('Chats per user, split by Website')
plt.xticks(rotation=60)
```

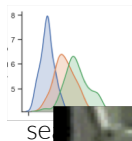
Elegant API, simple code structure,  
but ...

...embarrassingly...

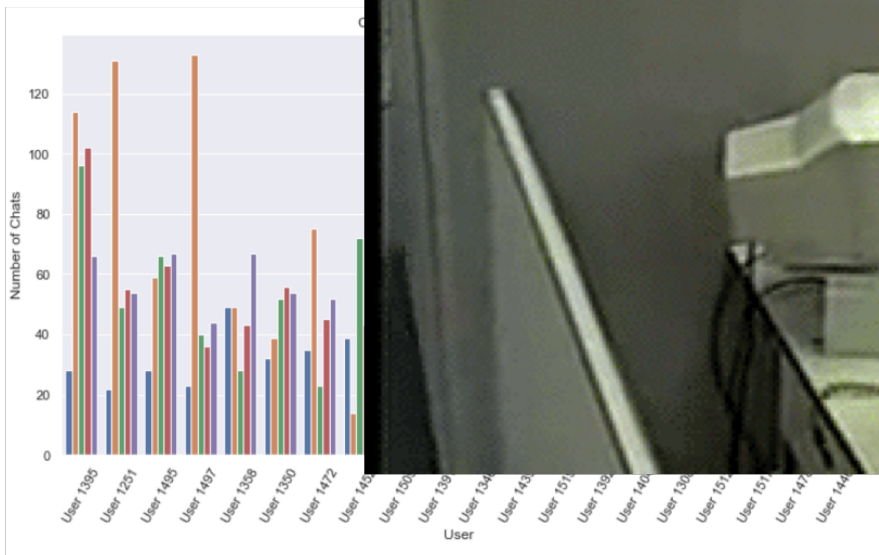
no stacked-bar chart support!



# Stacked Bar - Seaborn



```
sns.set()  
sns.barplot(x='user_id',
```



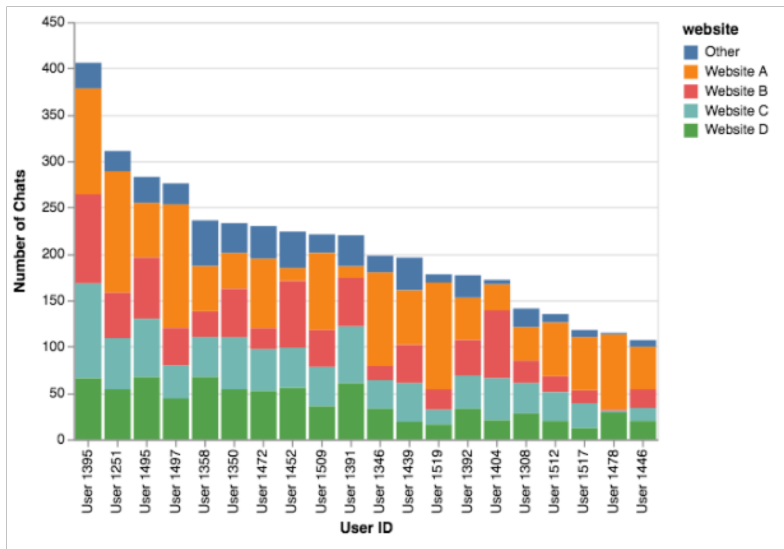
y Website')

cture,

!



# Stacked Bar - Altair



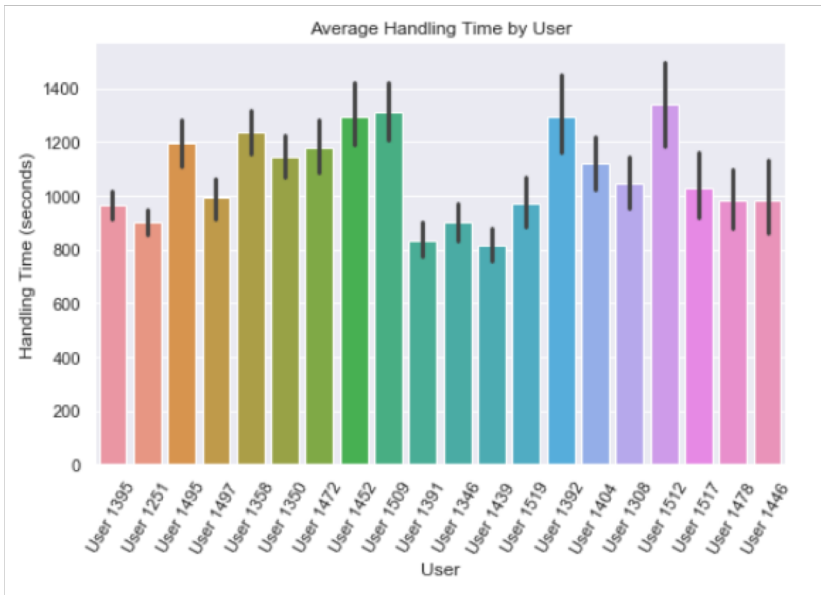
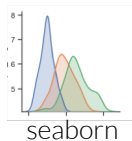
```
alt.Chart(  
  chats_per_user      # choose dataset here.  
) .mark_bar().encode(  
  x=alt.X(  
    'user_id',      # user_id on X Axis  
    sort=alt.EncodingSortField(field='number_chats',  
                                op='sum',  
                                order='descending'),  
    axis=alt.Axis(title='User ID')  
  ),  
  y=alt.Y('sum(number_chats)', # Sum of chats on y-axis  
          axis=alt.Axis(title='Number of Chats')),  
  color='website'  
)
```

Simple output, short code.

Some issues around data storage,  
JSON formats, and sorting is difficult.



# Seaborn - Estimators



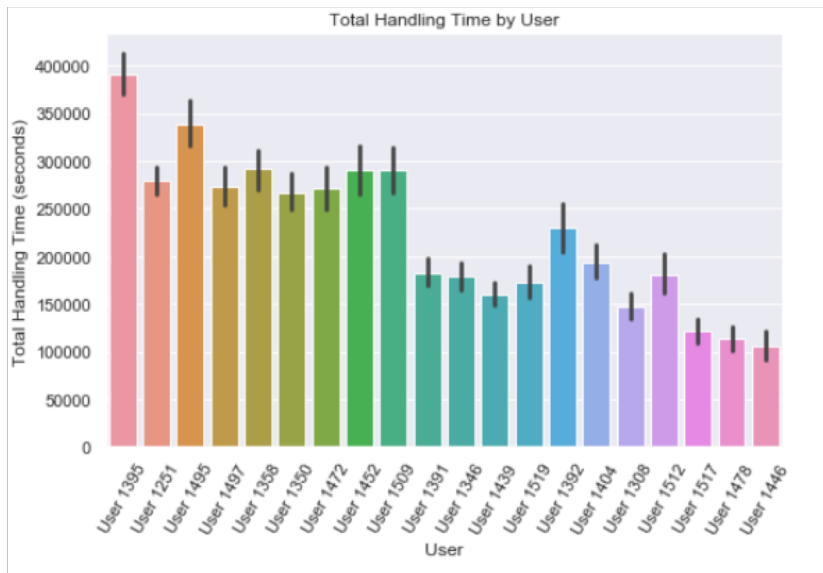
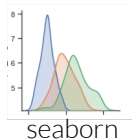
```
sns.barplot(  
    x='user_id', y='handling_time', estimator=np.mean,  
    data=data,  
    order=data['user_id'].value_counts().index.tolist()[0:20]  
)  
plt.xlabel('User')  
plt.ylabel('Handling Time (seconds)')  
plt.title('Average Handling Time by User')  
plt.xticks(rotation=60)
```

Calculations done as part of plotting – no previous data manipulations.

Separation of data and visualisation code.



# Seaborn - Estimators



```
sns.barplot(  
    x='user_id', y='handling_time', estimator=np.sum,  
    data=data,  
    order=data['user_id'].value_counts().index.tolist()[0:20]  
)  
plt.xlabel('User')  
plt.ylabel('Total Handling Time (seconds)')  
plt.title('Total Handling Time by User')  
plt.xticks(rotation=60)
```

Very simple to change estimator function to calculate different statistics.

Similar functionality available in Altair





# Histograms

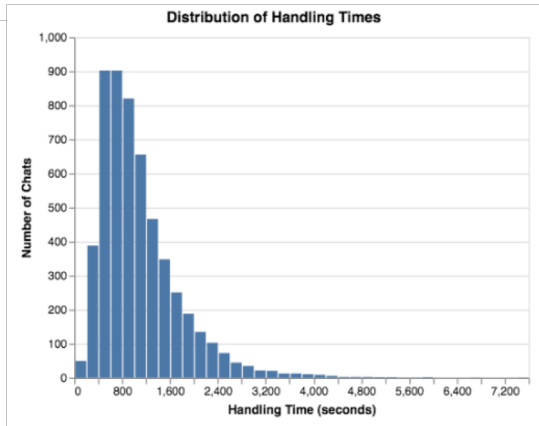
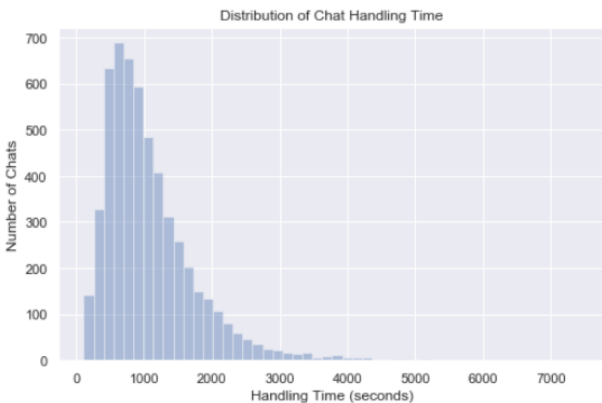




# Histograms



All libraries  
good at  
univariate  
distribution  
visualisations.



```
data['handling_time'].hist(bins=50)
plt.xlabel('Handling Time (seconds)')
plt.ylabel('Number of Chats')
plt.title("Distribution of Chat Handling Time")
```



```
sns.distplot(a=data['handling_time'],
             hist=True,
             kde=False,
             bins=50)
```



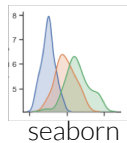
```
plt.xlabel('Handling Time (seconds)')
plt.ylabel('Number of Chats')
plt.title("Distribution of Chat Handling Time")
```

```
alt.Chart(data,
          title='Distribution of Handling Times'
          ).mark_bar().encode(
    x=alt.X(
      'handling_time', bin={'maxbins': 50},
      axis=alt.Axis(title='Handling Time (seconds)'),
    ),
    y=alt.Y(
      'count()',
      axis=alt.Axis(title='Number of Chats')
    )
  )
```



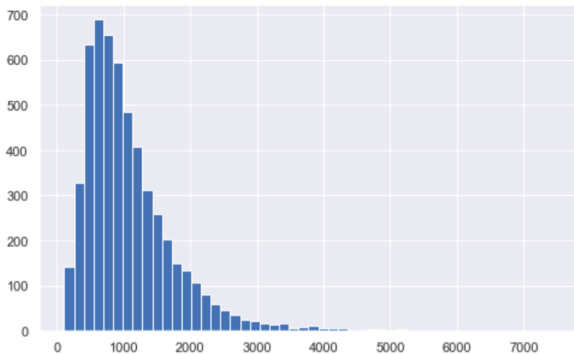


# Histograms



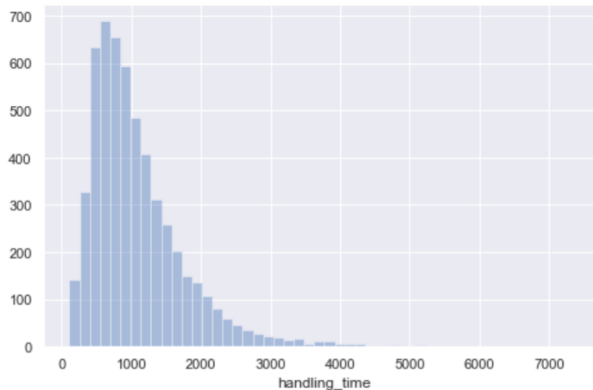
```
data['handling_time'].hist(bins=50)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x118526438>
```

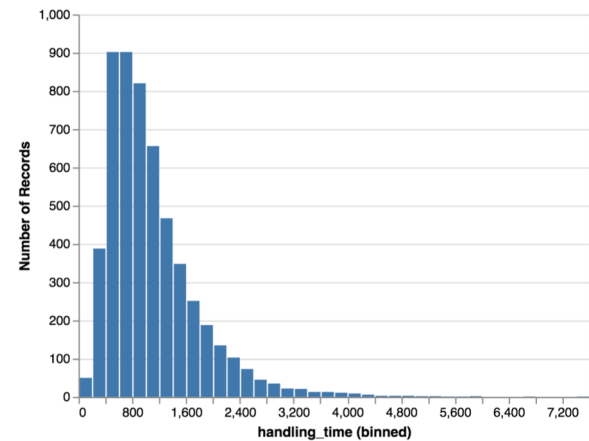


```
sns.distplot(a=data['handling_time'],  
             hist=True, kde=False, bins=50)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x118a3c400>
```



```
alt.Chart(data).mark_bar().encode(  
  x=alt.X('handling_time', bin={'maxbins': 50}),  
  y='count()' )
```



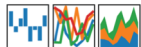


# Histograms



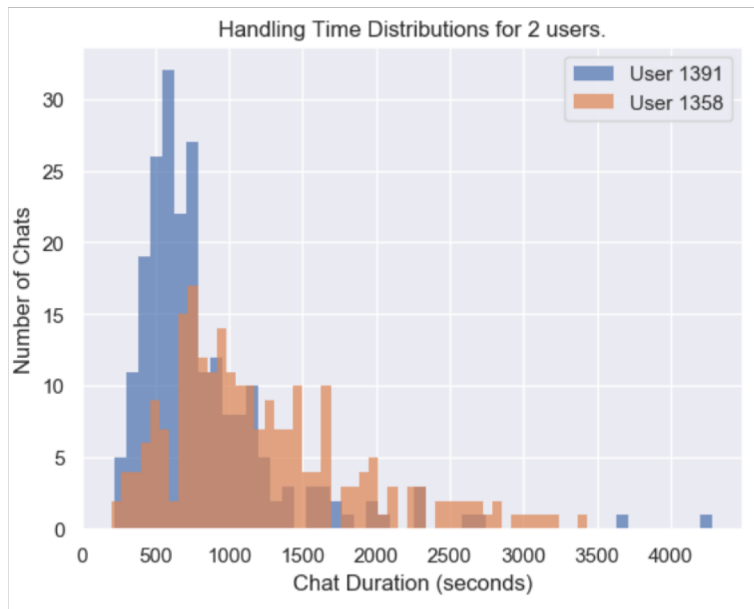
pandas

$$y_t = \beta'x_{it} + \mu_i + \epsilon_{it}$$



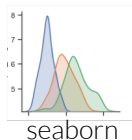
Layering / comparison achieved unfortunately by building up the histograms in place.

```
data.loc[data['user_id'] == 'User 1391', 'handling_time'].hist(  
    bins=50, alpha=0.7, label='User 1391')  
data.loc[data['user_id'] == 'User 1358', 'handling_time'].hist(  
    bins=50, alpha=0.7, label='User 1358')  
plt.legend()  
plt.title("Handling Time Distributions for 2 users.")  
plt.ylabel("Number of Chats")  
plt.xlabel("Chat Duration (seconds)")
```



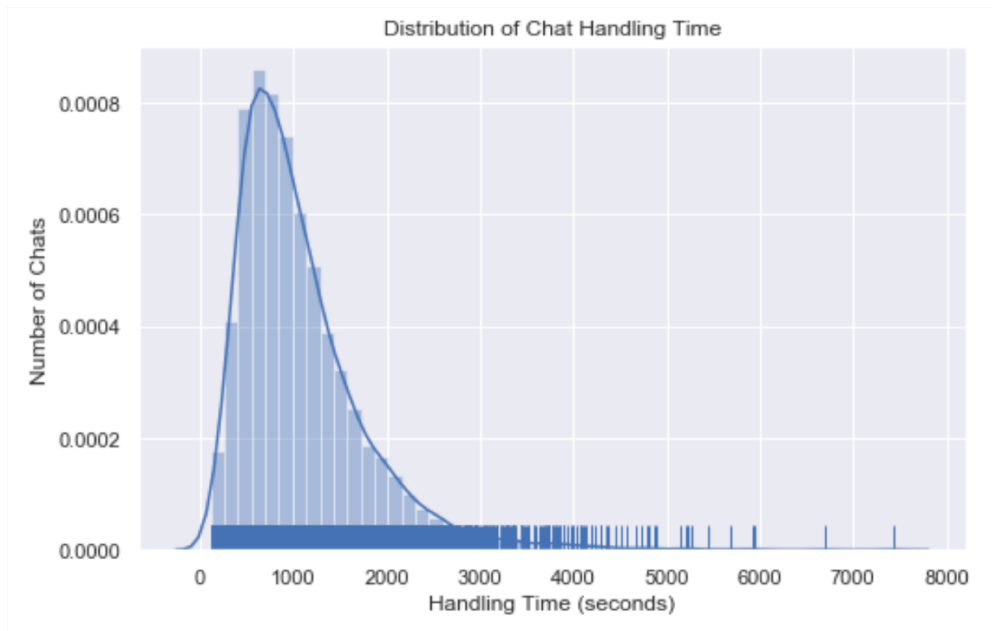


# Histograms - Seaborn



```
sns.distplot(a=data['handling_time'],  
             hist=True,  
             kde=True,  
             rug=True,  
             bins=50)  
plt.xlabel('Handling Time (seconds)')  
plt.ylabel('Number of Chats')  
plt.title("Distribution of Chat Handling Time")
```

Some really nice options for impressive and informative hints on Seaborn graphs.





# Scatter Plots - Pandas





# Scatter Plots - Pandas



Pandas: Good for quick single-coloured scatter visualisations.  
Messy with multiple categories.

```
colours = {
    "Website A": 'red',
    "Website B": 'blue',
    "Website C": 'green',
    "Website D": 'black',
    "Other": 'orange'
}
data.plot(
    x='handling_time',
    y='number_messages',
    kind='scatter',
    c=data['website_summary'].apply(lambda x: colours[x])
)
plt.xlabel("Handling Time (seconds)")
plt.ylabel("Messages in chat")
plt.title("Handling time vs Messages in chats")
```





# Scatter Plots - Pandas



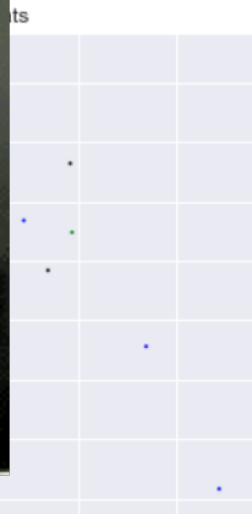
pandas



Pandas: Good for quick single-coloured scatter visualisations.

More with multiple categories

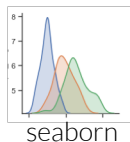
```
colours = {
    "Website A": 'red'
    "Website B": 'blue'
    "Website C": 'green'
    "Website D": 'black'
    "Other": 'orange'
}
data.plot(
    x='handling_time'
    y='number_message'
    kind='scatter',
    c=data['website_s
    )
plt.xlabel("Handling
plt.ylabel("Messages in chat")
plt.title("Handling time vs Messages in chats")
```







# Scatter Plots - Seaborn



Seaborn / Altair: Better higher level representation, and better for multi-category scatters.

```
sns.lmplot(  
    x='handling_time',  
    y='number_messages',  
    hue='website_summary',  
    data=data,  
    fit_reg=False, # SNS fits a regression line by default  
    scatter_kws={"s": 1}, # Size of point on figure  
)  
plt.title("Handling Time vs Number of Messages")  
plt.xlabel("Handling Time (seconds)")  
plt.ylabel("Number of Messages")
```





# Scatter Plots - Altair



Seaborn / Altair: Better higher level representation, and better for multi-category scatters.

```
alt.Chart(  
  data,  
  title='Handling Time vs Number of Messages'  
)  
.mark_point().encode(  
  x=alt.X('handling_time', title='Handling Time (seconds)'),  
  y=alt.Y('number_messages', title='Number of Messages'),  
  color='website_summary',  
  tooltip='user_id'  
)  
.interactive()
```





# Line Plots

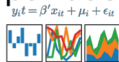




# Line Plots



pandas



Plot chats per language  
over time

Pandas: Needs data  
manipulation, simple  
thereafter.

```
plot_data = data\  
    .groupby(['date', 'language'])['chat_id']\  
    .count()\  
    .reset_index()\  
    .sort_values('date')  
plot_data.columns = ['date', 'language', 'number_chats']
```

```
plot_data.head()
```

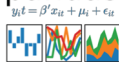
	date	language	number_chats
0	2018-05-30	English	24
1	2018-05-31	English	52
2	2018-06-01	English	37
3	2018-06-02	English	4
4	2018-06-03	English	9



# Line Plots



pandas



Pandas: Needs data manipulation, simple thereafter.

```
# Pandas again, for multiple lines requires data manipulation
pandas_plot = plot_data.pivot(
    index='date',
    columns='language',
    values='number_chats'
).fillna(0)
```

	date	language	number_chats
0	2018-05-30	English	24
1	2018-05-31	English	52
2	2018-06-01	English	37
3	2018-06-02	English	4
4	2018-06-03	English	9



```
plot_data = data\
    .groupby(['date', 'language'])['chat_id']\
    .count()\
    .reset_index()\
    .sort_values('date')
plot_data.columns = ['date', 'language', 'number_chats']
```

```
plot_data.head()
```

language	English	French	German	Italian	Portuguese	Spanish	Swedish	Turkish
date								
2018-05-30	24.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2018-05-31	52.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2018-06-01	37.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2018-06-02	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2018-06-03	9.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2018-06-04	141.0	1.0	0.0	0.0	1.0	1.0	0.0	0.0
2018-06-05	156.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2018-06-06	223.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0
2018-06-07	297.0	1.0	1.0	1.0	0.0	0.0	1.0	1.0





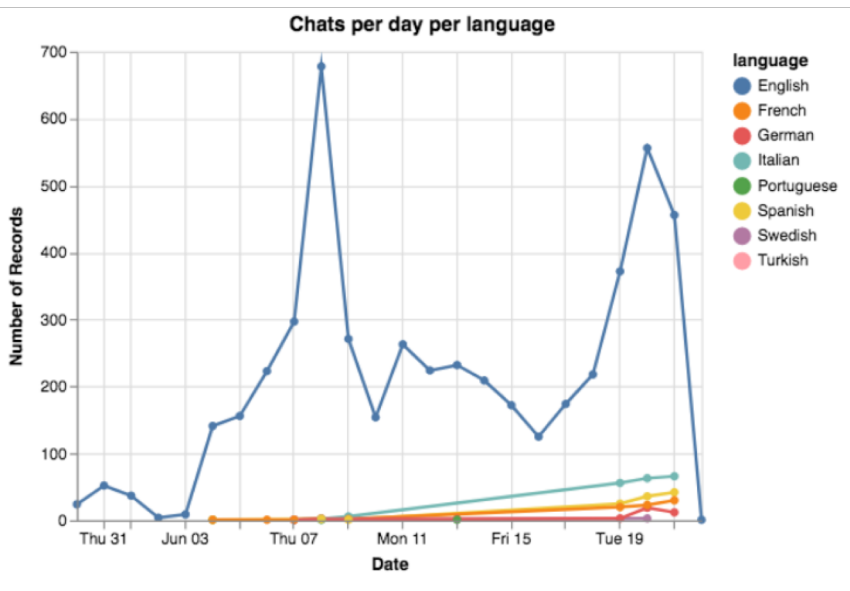
# Line Plots



Seaborn/Altair:  
Operate directly on  
raw data



```
# Seaborn can act directly on the raw data!  
sns.lineplot(  
    x='date',  
    y='chat_id',  
    hue='language',  
    data=data,  
    estimator=len,  
    marker='o'  
)  
  
# Formatting of plot output  
plt.xlabel("Date")  
plt.xticks(rotation=90)  
plt.ylabel("Number Chats")  
plt.title("Chats per day per language")
```



```
# Altair works directly on the raw data  
alt.Chart(  
    data,  
    title='Chats per day per language'  
)  
.mark_line(point=True).encode(  
    x=alt.X('date', title='Date'),  
    y='count(chat_id)',  
    color='language'  
)
```

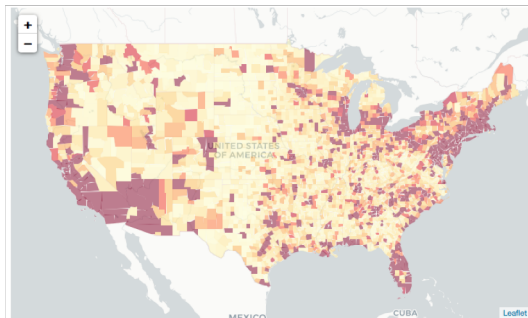


# More Options!

## Geospatial Viz

Folium: Generate interactive maps using leaflet.js

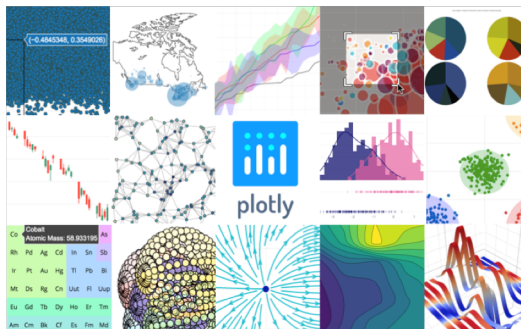
Matplotlib: Basemap plugin



## Interactive Plots

Bokeh: Makes visualisations for web browser interaction.

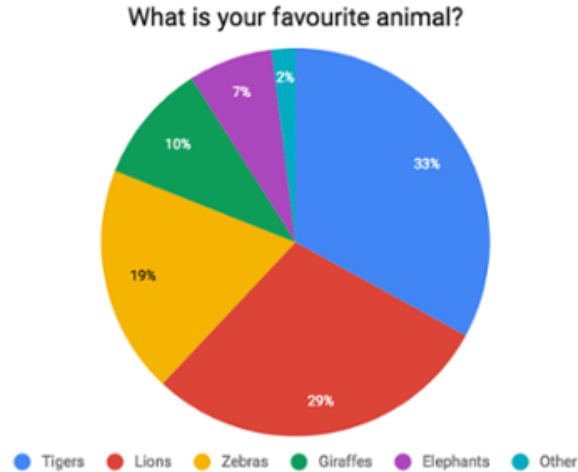
Plotly: Online visualisations – runs by default in cloud







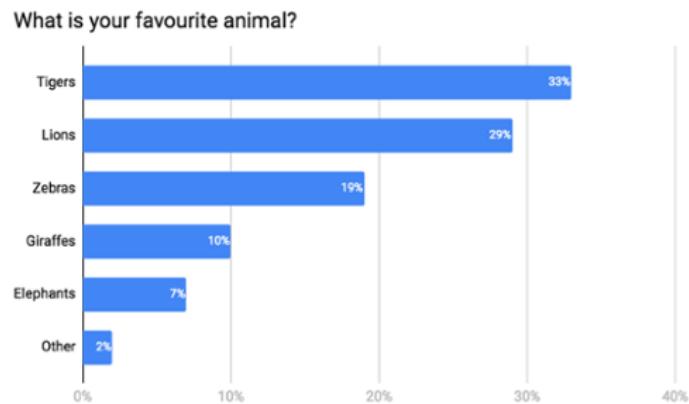
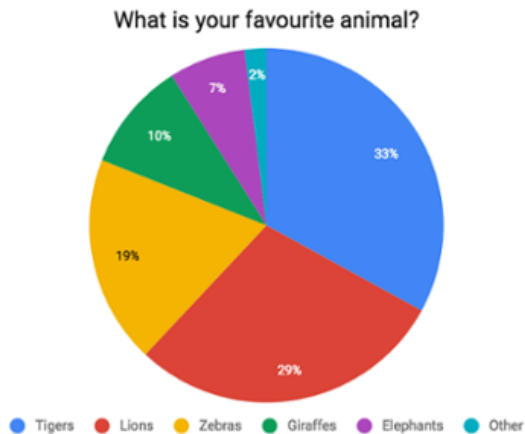
# What to Avoid – Angles?



**Pie Charts:** Radial angle for comparison. Humans are very bad at accurate radial comparisons – we've evolved for speedy length / distance comparisons.



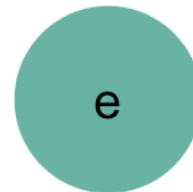
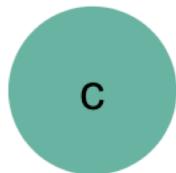
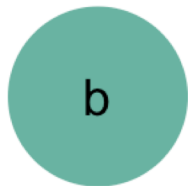
# What to Avoid – Angles?



**Pie Charts:** Radial angle for comparison. Humans are very bad at accurate radial comparisons – we've evolved for speedy length / distance comparisons.



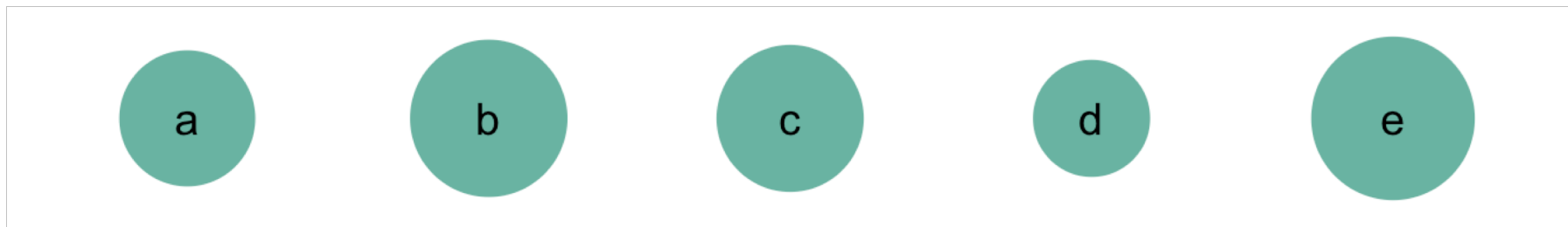
# What to Avoid – Area?



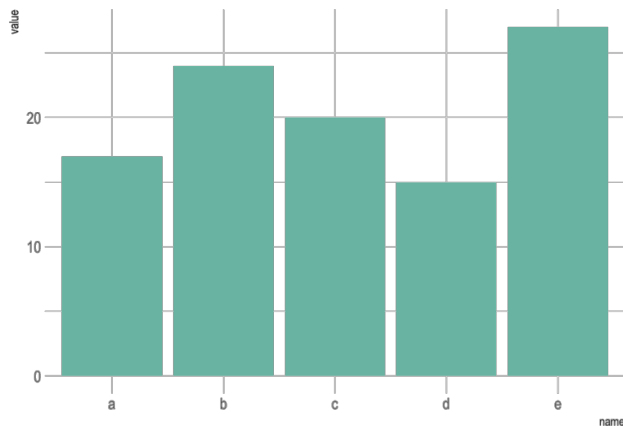
**Area:** We're bad at area – rank these bubbles by area, and compare them relative to each other.



# What to Avoid – Area?



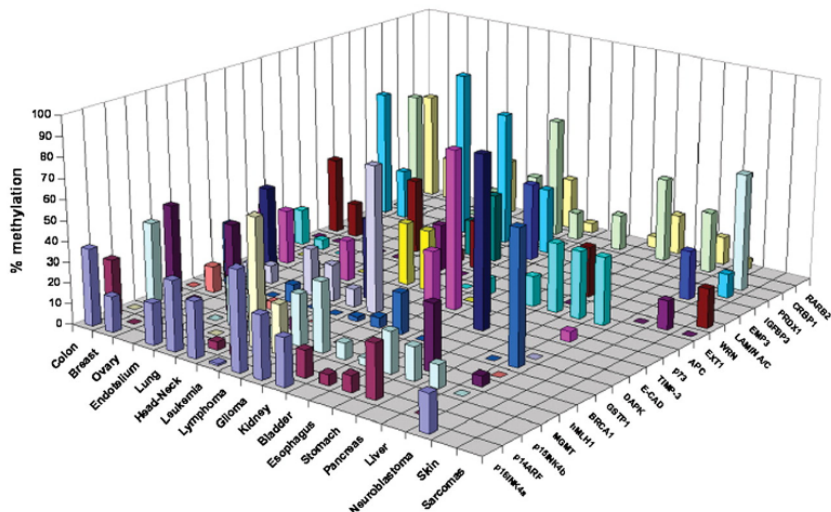
**Area:** We're bad at area – rank these bubbles by area, and compare them relative to each other.



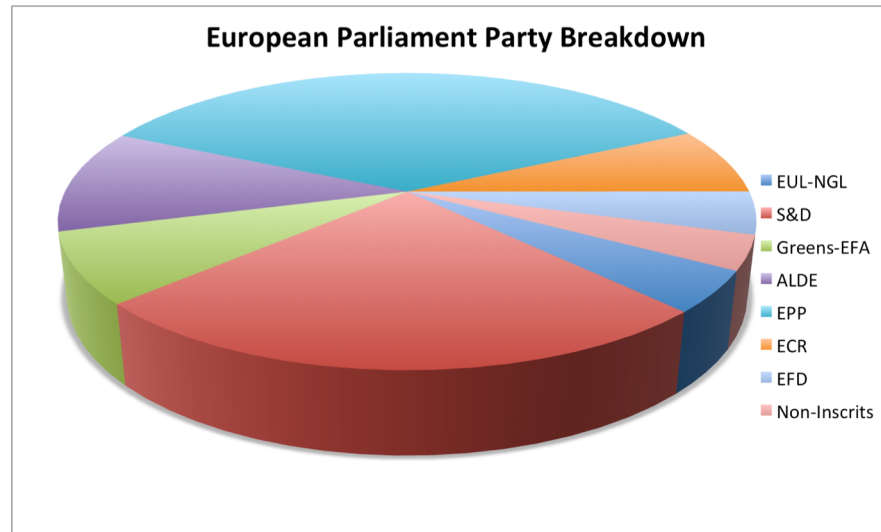


# What to Avoid – 3d?

A CpG Island Hypermethylation Profile of Human Cancer



European Parliament Party Breakdown



3d: In general, 3D is “fake fancy”. Impractical but gee-whizz – avoid!

Caveat: Interactive Scatters?



# Conclusions

Wide variety of tools available in Python.

Get familiar with Pandas syntax for quick & simple exploration, and use with Seaborn themes.

Learn one more high-level library in detail – Seaborn or Altair for publication of output and more flexibility

“Simplicity is the ultimate sophistication”

*Leonardo Da Vinci*



COMPLEX DECISIONS SIMPLIFIED

# Data Visualisation in Python

Quick and easy routes to plotting magic

Shane Lynn PhD

@shane\_a\_lynn | @TeamEdgeTier



[www.edgetier.com](http://www.edgetier.com) | [info@edgetier.com](mailto:info@edgetier.com) | [@TeamEdgeTier](https://twitter.com/TeamEdgeTier)



# More?

## Resources

Tour of Python's Data Landscape

<https://dsaber.com/2016/10/02/a-dramatic-tour-through-pythons-data-visualization-landscape-including-ggplot-and-altair/>

Python Graph Gallery

<https://python-graph-gallery.com/>

From Data to Viz

<https://www.data-to-viz.com/>