# Summarize your data with descriptive stats

IMPORTING AND MANAGING FINANCIAL DATA IN PYTHON

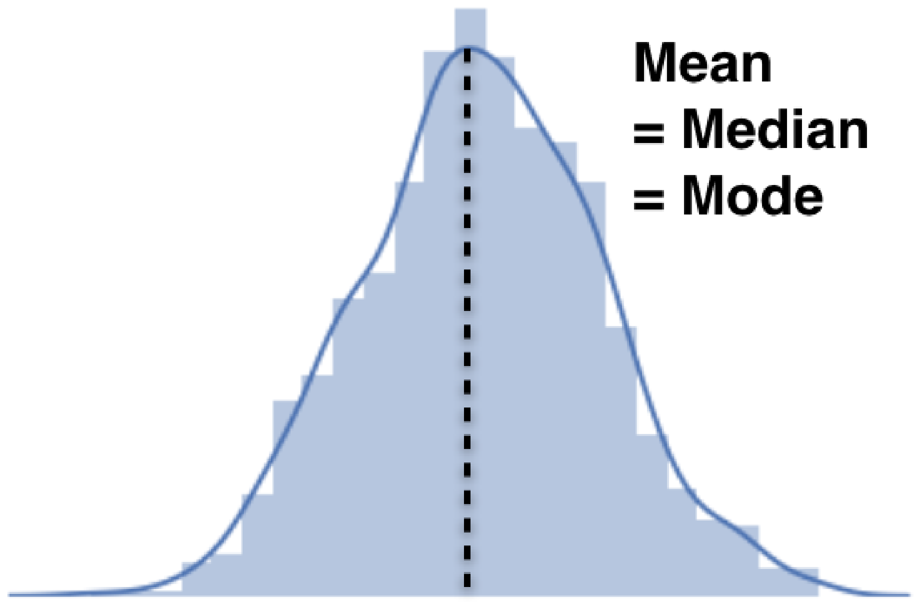
Stefan Jansen
Instructor

# Be on top of your data

- Goal: Capture key quantitative characteristics
- Important angles to look at:
  - Central tendency: Which values are "typical"?
  - Dispersion: Are there outliers?
  - Overall distribution of individual variables

# Central tendency

- Mean (average): $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$
- Median: 50% of values smaller/larger
- Mode: most frequent value



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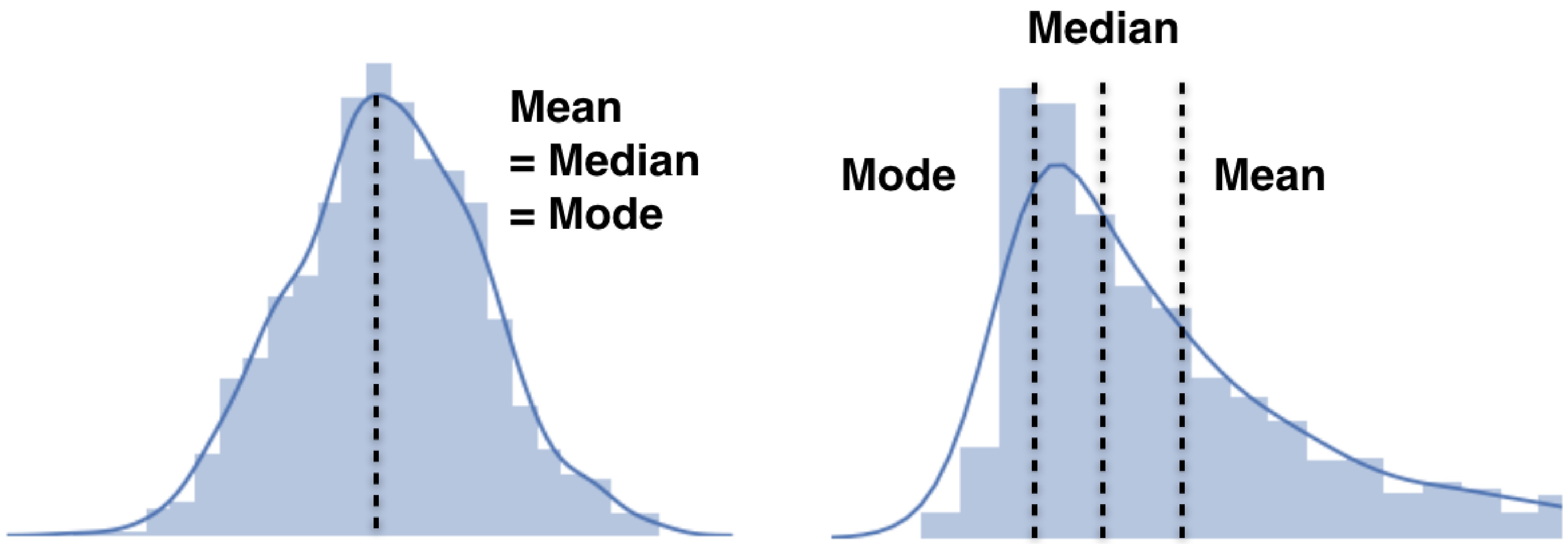

# Central tendency

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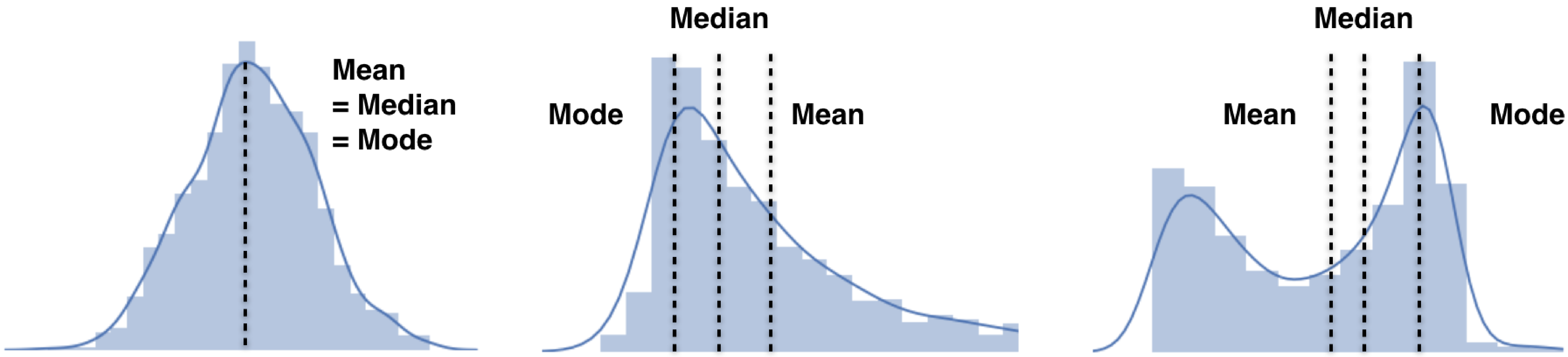


# Calculate summary statistics

```
nasdaq = pd.read_excel('listings.xlsx', sheet_name='nasdaq', na_values='n/a')
market_cap = nasdaq['Market Capitalization'].div(10**6)
```

```
market_cap.mean()
```

```
3180.7126214953805
```

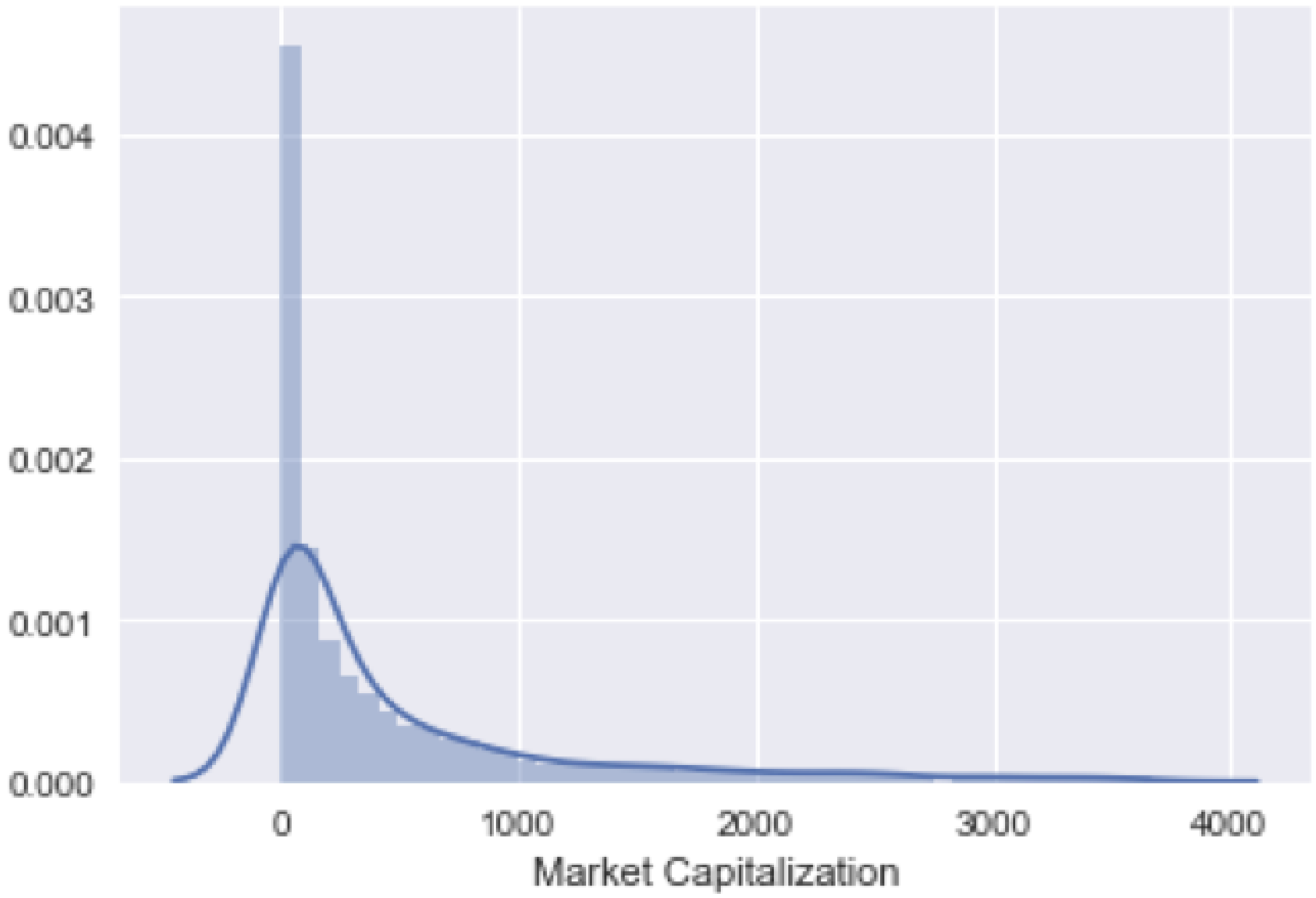
```
market_cap.median()
```

```
225.9684285
```

```
market_cap.mode()
```

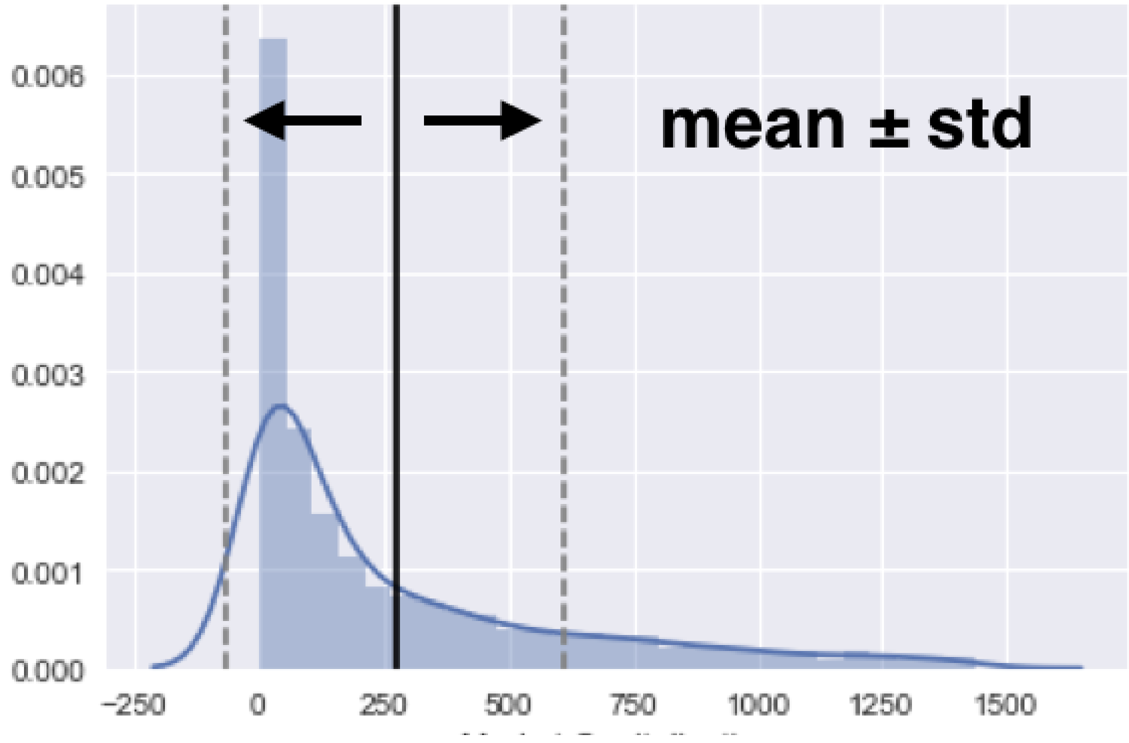
```
0.0
```

# Calculate summary statistics



# Dispersion

- **Variance:** Sum all of the squared differences from mean and divide by $n-1$
  - $var = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2$
- **Standard deviation:** Square root of variance
  - $sd = \sqrt{var}$



# Calculate variance and standard deviation

```
variance = market_cap.var()
print(variance)
```

```
648773812.8182
```

```
np.sqrt(variance)
```

```
25471.0387
```

```
market_cap.std()
```

```
25471.0387
```

# Let's practice!

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# Describe the distribution of your data with quantiles

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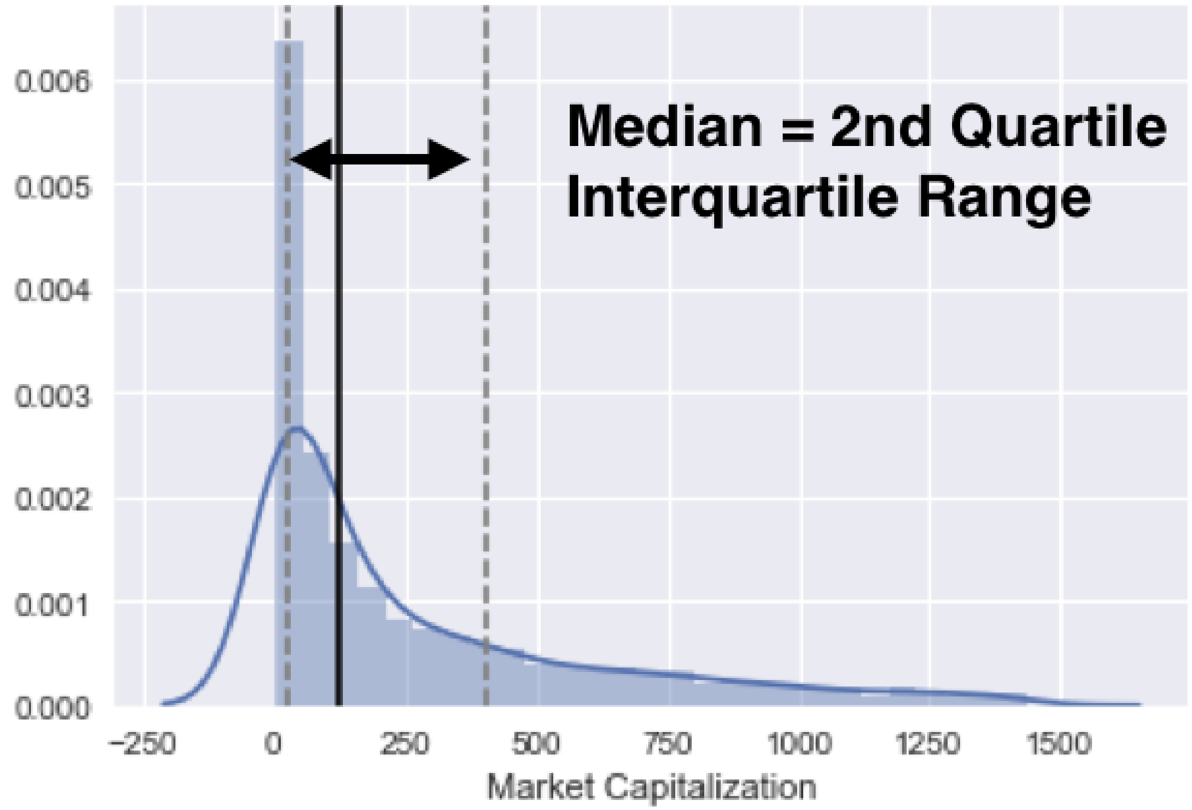
# Describe data distributions

- First glance: Central tendency and standard deviation
- How to get a more granular view of the distribution?
- Calculate and plot quantiles

# More on dispersion: quantiles

- Quantiles: Groups with equal share of observations
  - Quartiles: 4 groups, 25% of data each
  - Deciles: 10 groups, 10% of data each
  - Interquartile range: 3rd quartile - 1st quartile



# Quantiles with pandas

```
market_cap = nasdaq['Market Capitalization'].div(10**6)
median = market_cap.quantile(.5)
median == market_cap.median()
```

```
True
```

```
quantiles = market_cap.quantile([.25, .75])
```

```
0.25     43.375930
0.75    969.905207
```

```
quantiles[.75] - quantiles[.25] # Interquartile Range
```

```
926.5292771575
```

# Quantiles with pandas & numpy

```
deciles = np.arange(start=.1, stop=.91, step=.1)
deciles
```

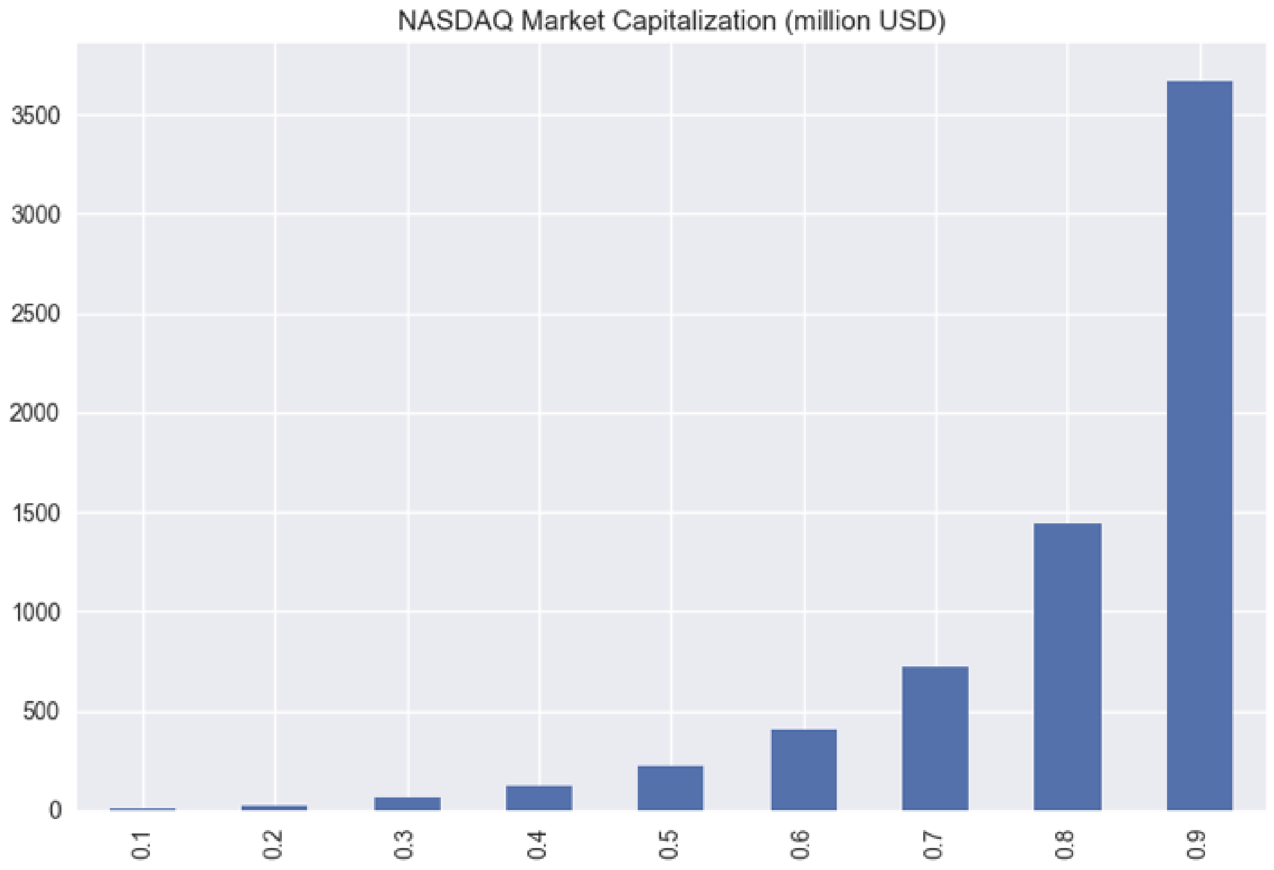
```
array([ 0.1,  0.2,  0.3,  0.4,  ..., 0.7,  0.8,  0.9])
```

```
market_cap.quantile(deciles)
```

```
0.1       4.884565
0.2      26.993382
0.3      65.714547
0.4     124.320644
0.5     225.968428
0.6     402.469678
...
```

# Visualize quantiles with bar chart

```
title = 'NASDAQ Market Capitalization (million USD)'
market_cap.quantile(deciles).plot(kind='bar', title=title)
plt.tight_layout(); plt.show()
```



# All statistics in one go

```
market_cap.describe()
```

```
count       3167.000000
mean        3180.712621
std        25471.038707
min            0.000000
25%           43.375930  # 1st quantile
50%          225.968428  # Median
75%          969.905207  # 3rd quantile
max       740024.467000
Name: Market Capitalization
```

# All statistics in one go

```
market_cap.describe(percentiles=np.arange(.1, .91, .1))
```

```
count       3167.000000
mean        3180.712621
std        25471.038707
min            0.000000
10%            4.884565
20%           26.993382
30%           65.714547
40%          124.320644
50%          225.968428
60%          402.469678
70%          723.163197
80%         1441.071134
...
```

# Let's practice!

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# Visualize the distribution of your data

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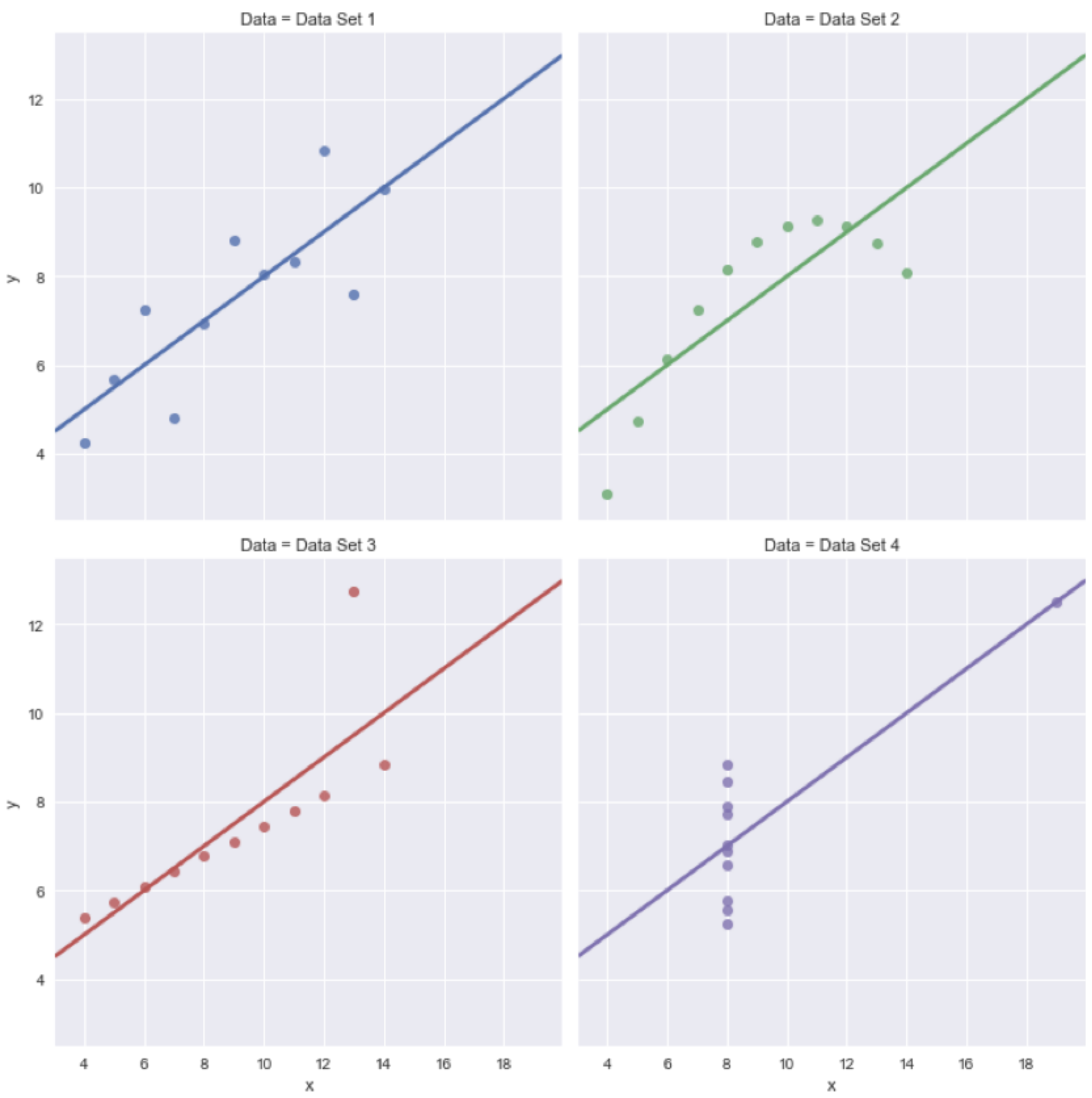
# Always look at your data!

- Identical metrics can represent very different data



# Introducing seaborn plots

- Many attractive and insightful statistical plots
- Based on `matplotlib`
- Swiss Army knife: `seaborn.distplot()`
  - Histogram
  - Kernel Density Estimation (KDE)
  - Rugplot

# 10 year treasury: trend and distribution

```
ty10 = web.DataReader('DGS10', 'fred', date(1962, 1, 1))
ty10.info()
```

```
DatetimeIndex: 15754 entries, 1962-01-02 to 2022-05-20
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
 --  ------  --------------  -----
 0   DGS10   15083 non-null  float64
```

```
ty10.describe()
```

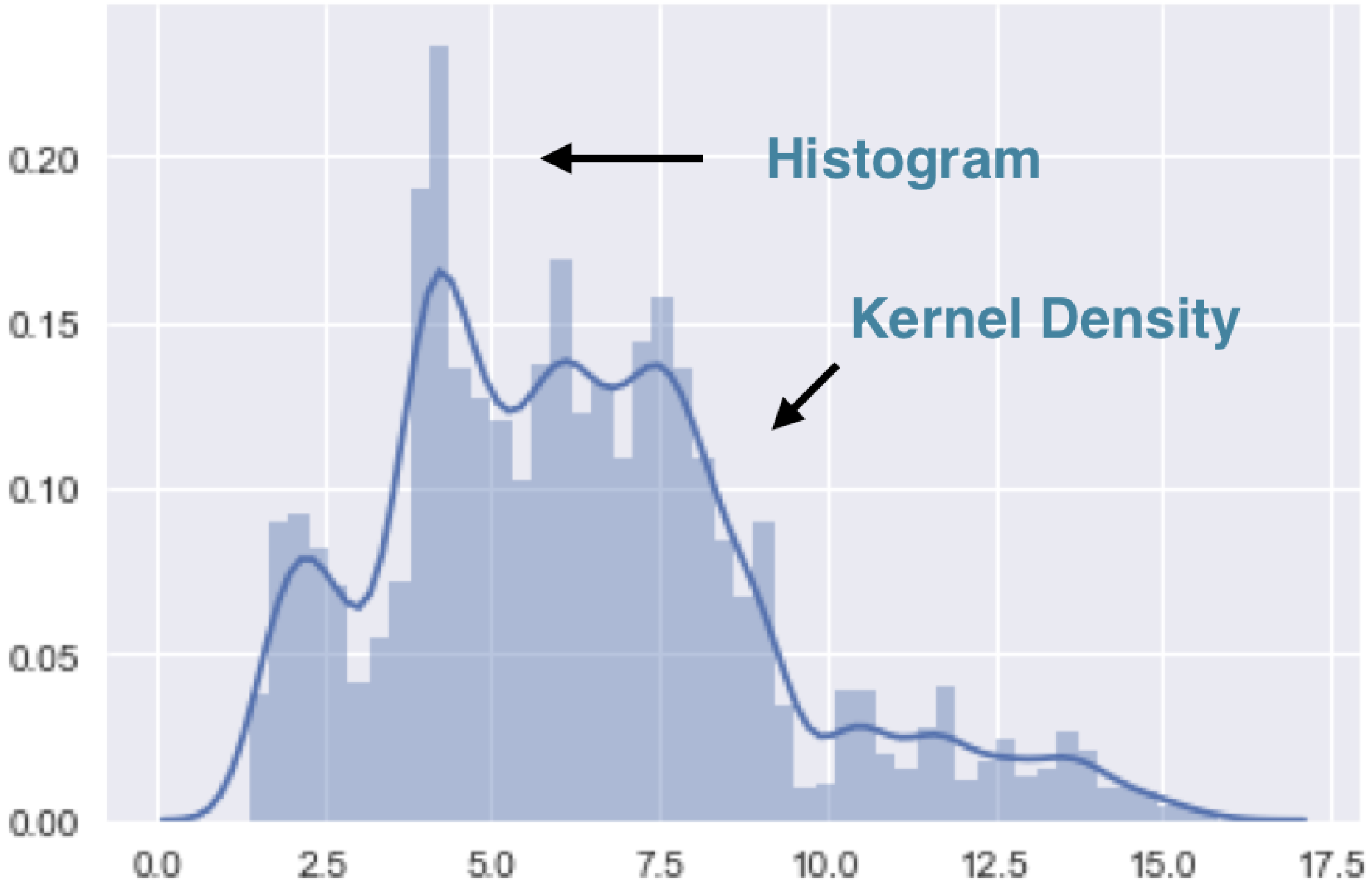
```
              DGS10
mean       6.291073
std        2.851161
min        1.370000
25%        4.190000
50%        6.040000
...
```

# 10 year treasury: time series trend

```
ty10.dropna(inplace=True) # Avoid creation of copy
ty10.plot(title='10-year Treasury'); plt.tight_layout()
```

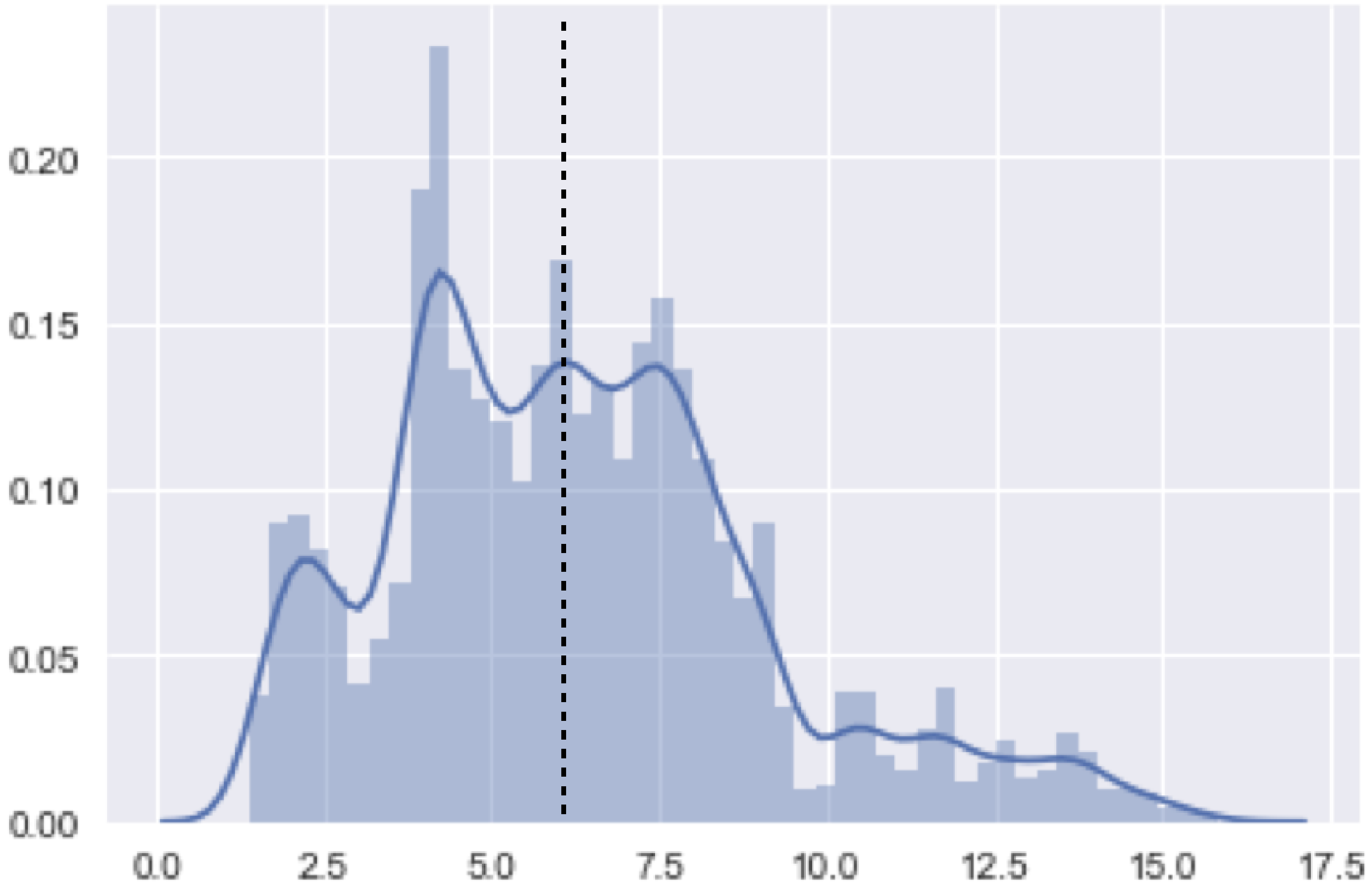
# 10 year treasury: historical distribution

```
import seaborn as sns
sns.distplot(ty10)
```



# 10 year treasury: trend and distribution

```
ax = sns.distplot(ty10)
ax.axvline(ty10['DGS10'].median(), color='black', ls='--')
```



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# Summarize categorical variables

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# From categorical to quantitative variables

- So far, we have analyzed quantitative variables
- Categorical variables require a different approach
- Concepts like average don't make much sense
- Instead, we'll rely on their frequency distribution

# Categorical listing information

```
amex = pd.read_excel('listings.xlsx', sheet_name='amex',
                     na_values=['n/a'])
amex.info()
```

```
RangeIndex: 360 entries, 0 to 359
Data columns (total 7 columns):
 #   Column                 Non-Null Count  Dtype
 --  ------                 --------------  -----
 0   Stock Symbol           360 non-null    object
 1   Company Name           360 non-null    object
 2   Last Sale              346 non-null    float64
 3   Market Capitalization  360 non-null    float64
 4   IPO Year               105 non-null    float64
 5   Sector                 238 non-null    object
 6   Industry               238 non-null    object
dtypes: float64(3), object(4)
```

# Categorical listing information

```
amex = amex['Sector'].nunique()
```

```
12
```

- `apply()` : call function on each column
- `lambda` : "anonymous function", receives each column as argument `x`

```
amex.Sector.apply(lambda x: x.nunique())
```

```
Stock Symbol             360
Company Name             326
Last Sale                323
Market Capitalization    317
...
```

# How many observations per sector?

```
amex['Sector'].value_counts()
```

```
Health Care              49 # Mode
Basic Industries         44
Energy                   28
Consumer Services        27
Capital Goods            24
Technology               20
Consumer Non-Durables    13
Finance                  12
Public Utilities         11
Miscellaneous             5
...
```

# How many IPOs per year?

```
amex['IPO Year'].value_counts()
```

```
2002.0    19 # Mode
2015.0    11
1999.0     9
1993.0     7
2014.0     6
2013.0     5
2017.0     5
...
2009.0     1
1990.0     1
1991.0     1
Name: IPO Year, dtype: int64
```

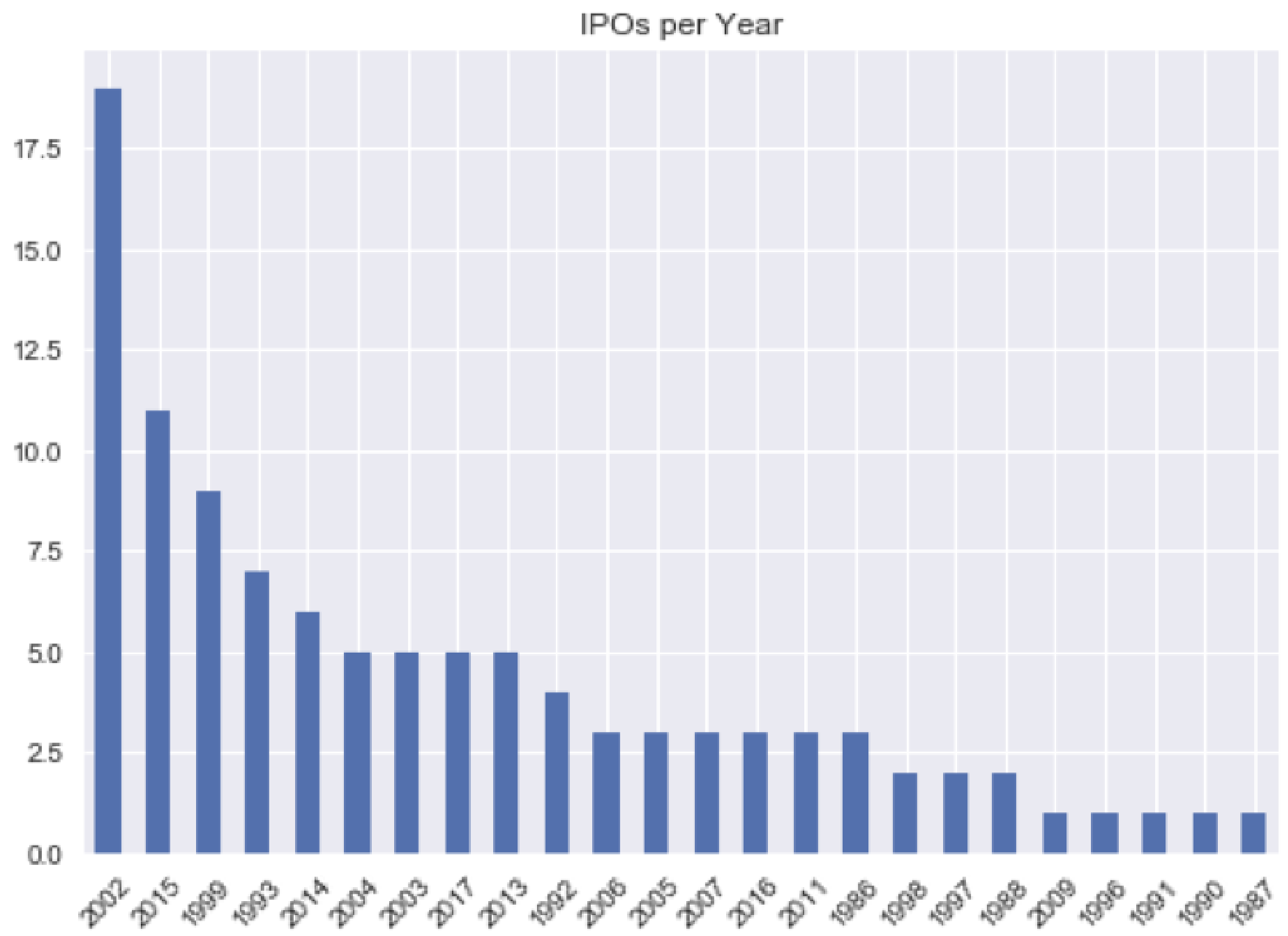
# Convert IPO Year to int

```
ipo_by_yr = amex['IPO Year'].dropna().astype(int).value_counts()
ipo_by_yr
```

```
2002    19
2015    11
1999     9
1993     7
2014     6
2004     5
2003     5
2017     5
...
1987     1
Name: IPO Year, dtype: int64
```

# Convert IPO Year to int

```
ipo_by_yr.plot(kind='bar', title='IPOs per Year')
plt.xticks(rotation=45)
```



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