

Extreme value theory

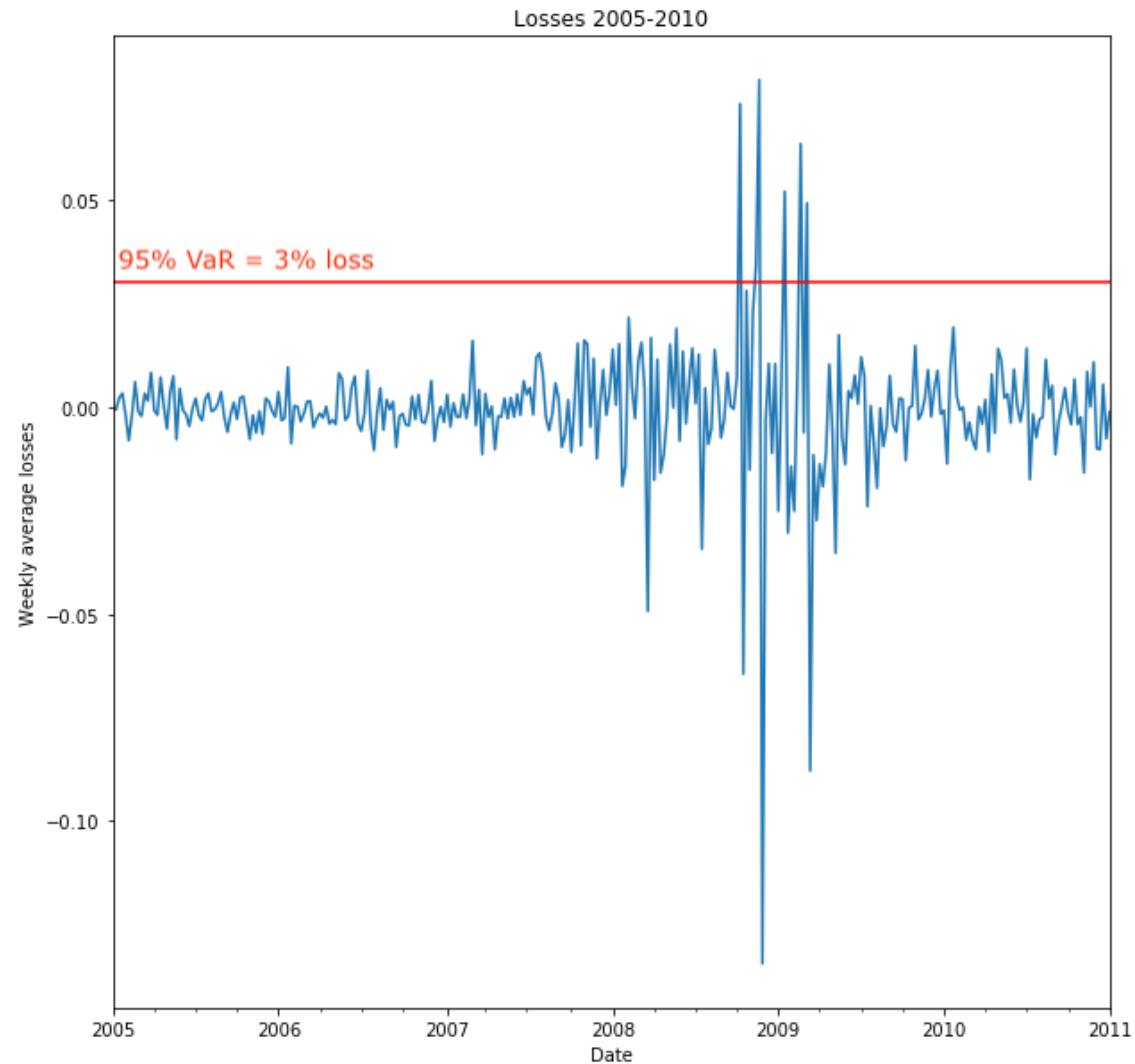
QUANTITATIVE RISK MANAGEMENT IN PYTHON



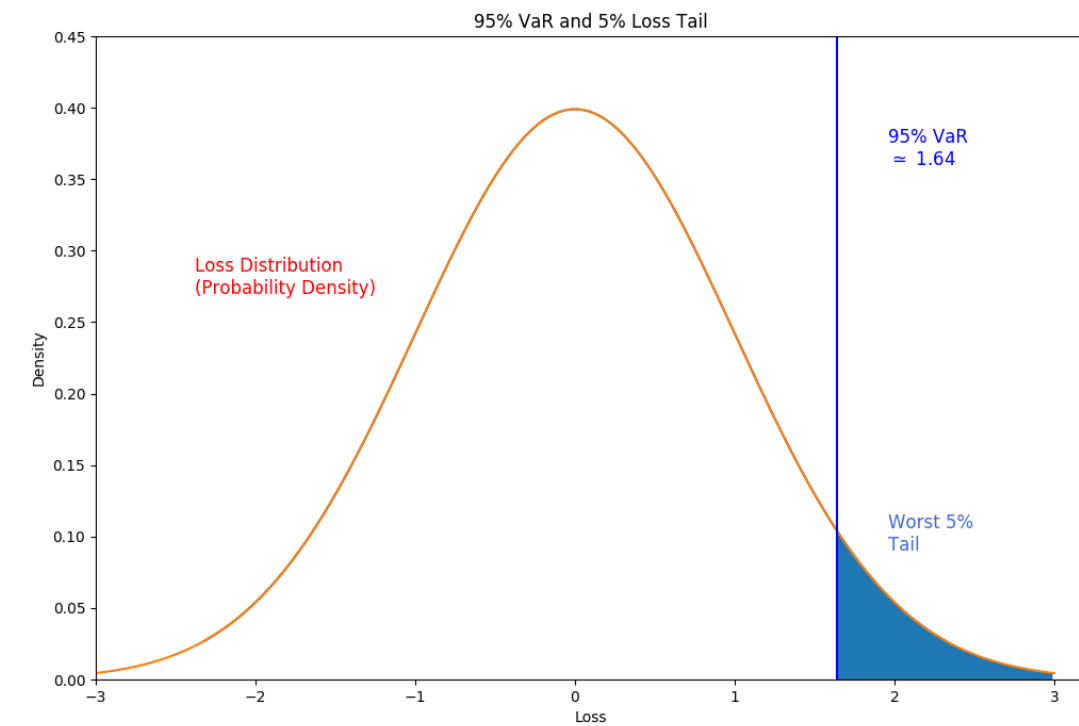
Jamsheed Shorish
Computational Economist

Extreme values

- Portfolio losses: extreme values



- Extreme values: from tail of distribution
 - Tail losses: losses exceeding some value
 - Model tail losses => better risk management



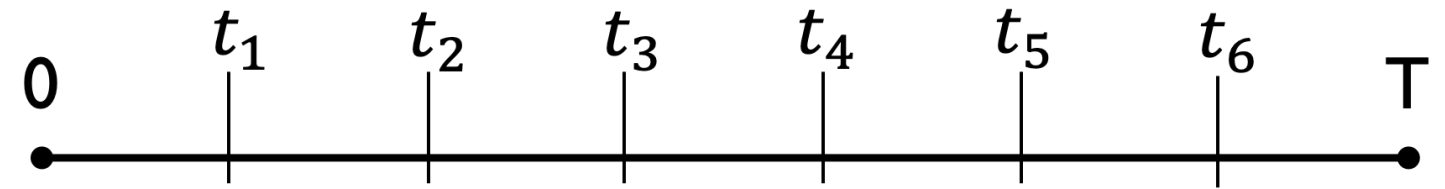
Extreme value theory

- **Extreme value theory:** statistical distribution of extreme values
- **Block maxima**



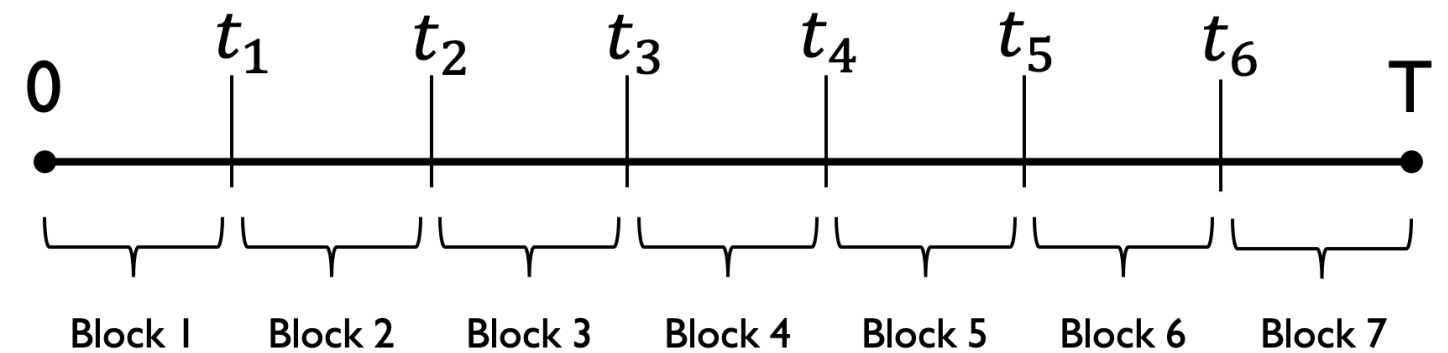
Extreme value theory

- **Extreme value theory:** statistical distribution of extreme values
- **Block maxima:**
 - Break period into sub-periods



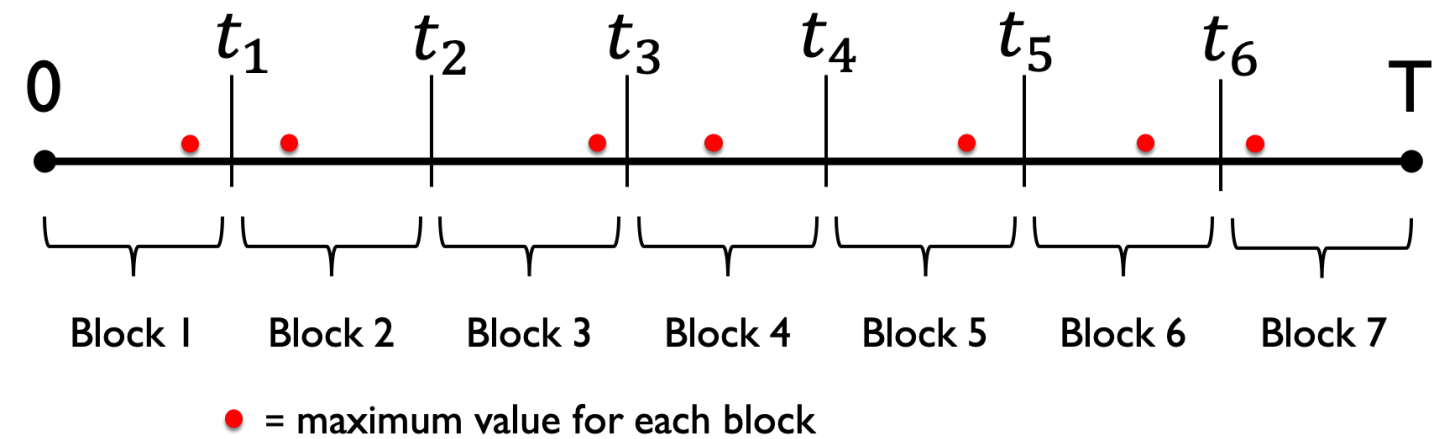
Extreme value theory

- **Extreme value theory:** statistical distribution of extreme values
- **Block maxima:**
 - Break period into sub-periods
 - Form *block* from each sub-period



Extreme value theory

- **Extreme value theory:** statistical distribution of extreme values
- **Block maxima:**
 - Break period into sub-periods
 - Form *blocks* from each sub-period
 - Set of block maxima = dataset
- **Peak over threshold (POT):**
 - Find all losses over given level
 - Set of such losses = dataset



Generalized Extreme Value Distribution

- **Example:** Block maxima for 2007 - 2009
 - Resample losses with desired period (e.g. weekly)

```
maxima = losses.resample("W").max()
```

- **Generalized Extreme Value Distribution (GEV)**
 - Distribution of *maxima* of data
 - Example: parametric estimation using `scipy.stats.genextreme`

```
from scipy.stats import genextreme  
params = genextreme.fit(maxima)
```

VaR and CVaR from GEV distribution

- **99% VaR** from GEV distribution
 - Use `.ppf()` percent point function to find 99% VaR
 - Requires `params` from fitted GEV distribution
 - Finds maximum loss over one week period at 99% confidence
- **99% CVaR** from GEV distribution
 - CVaR is conditional expectation of loss *given* VaR as minimum loss
 - Use `.expect()` method to find expected value

```
VaR_99 = genextreme.ppf(0.99, *params)
```

```
CVaR_99 = ( 1 / (1 - 0.99) ) * genextreme.expect(lambda x: x, *params, lb = VaR_99)
```


Covering losses

- **Risk management:** *covering losses*
 - Regulatory requirement (banks, insurance)
 - Reserves must be available to cover losses
 - For a specified period (e.g. one week)
 - At a specified confidence level (e.g. 99%)
- **VaR from GEV distribution:**
 - estimates maximum loss
 - given period
 - given confidence level

Covering losses

- **Example:** Initial portfolio value = \$1,000,000
- **One week reserve requirement** at 99% confidence
 - VaR_{99} from GEV distribution: maximum loss over one week at 99% confidence
- **Reserve requirement:** Portfolio value $\times VaR_{99}$
 - Suppose $VaR_{99} = 0.10$, i.e. 10% maximum loss
 - Reserve requirement = \$100,000
- Portfolio value *changes* \Rightarrow reserve requirement *changes*
- **Regulation** sets frequency of reserve requirement updating

Let's practice!

QUANTITATIVE RISK MANAGEMENT IN PYTHON

Kernel density estimation

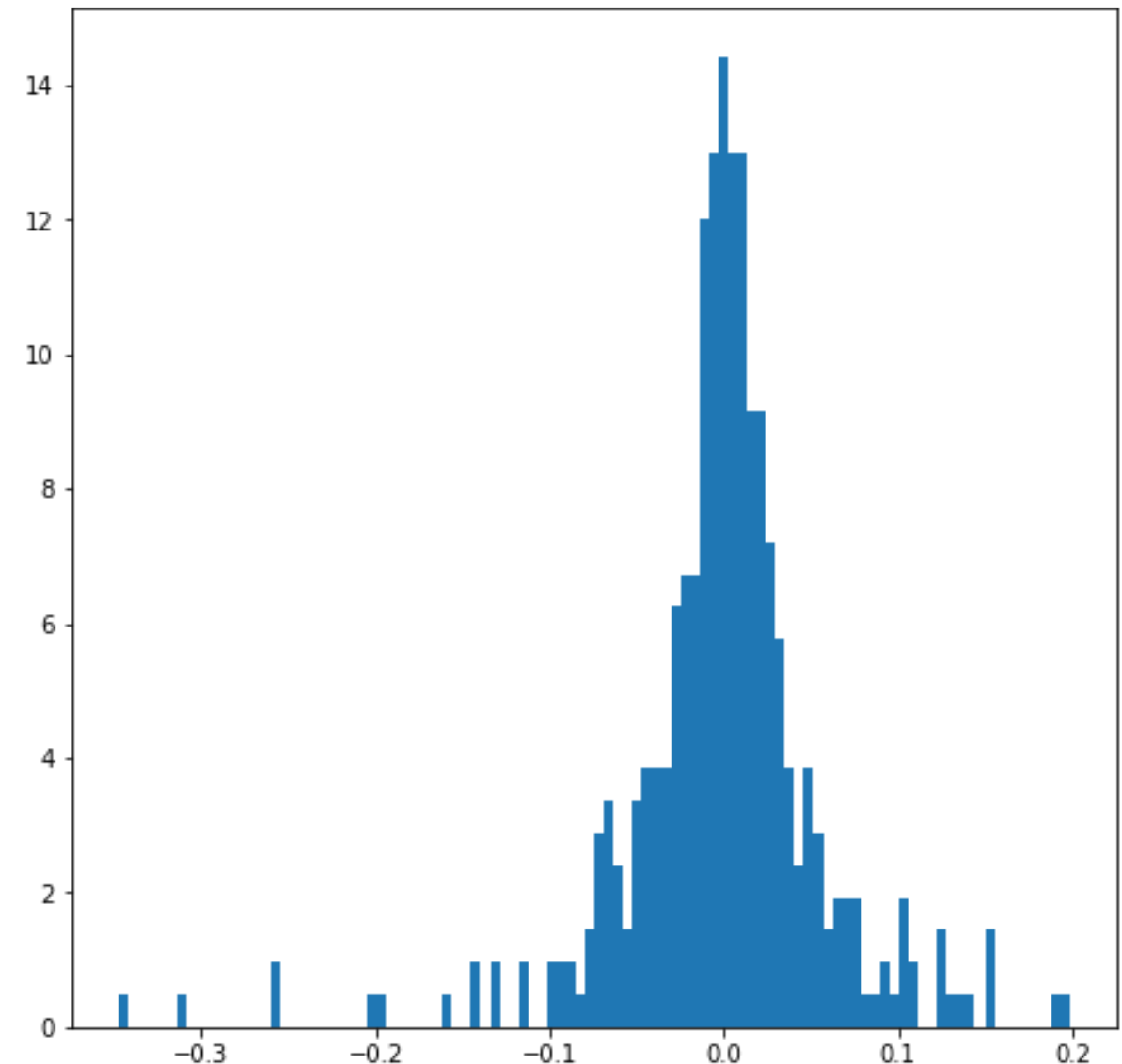
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The histogram revisited

- **Risk factor distributions**
 - *Assumed* (e.g. Normal, T, etc.)
 - *Fitted* (parametric estimation, Monte Carlo simulation)
 - *Ignored* (historical simulation)
- **Actual data:** histogram
- How to represent histogram by probability distribution?
 - *Smooth* data using **filtering**
 - **Non-parametric estimation**



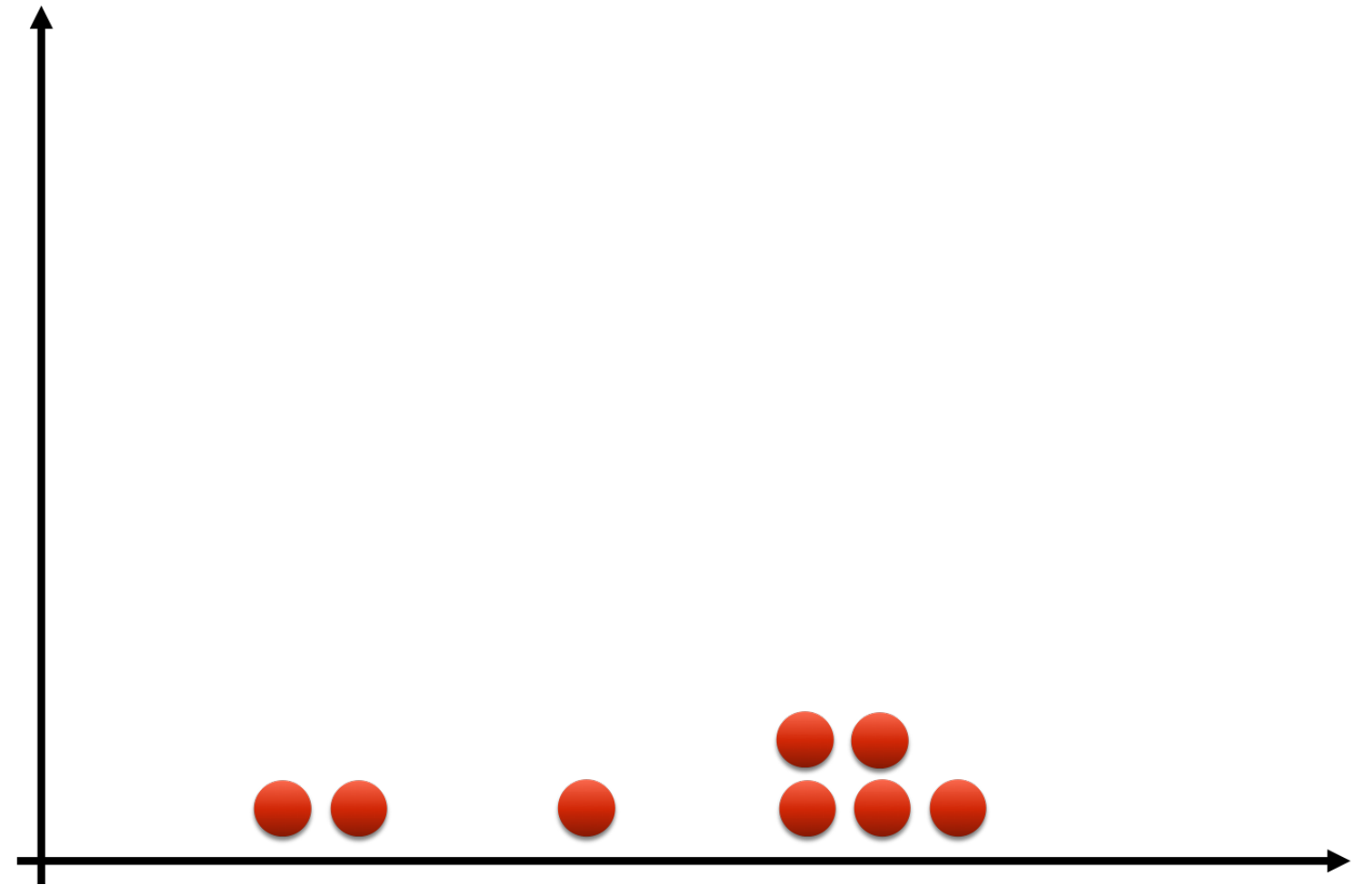
Data smoothing

- **Filter:** smoothen out 'bumps' of histogram



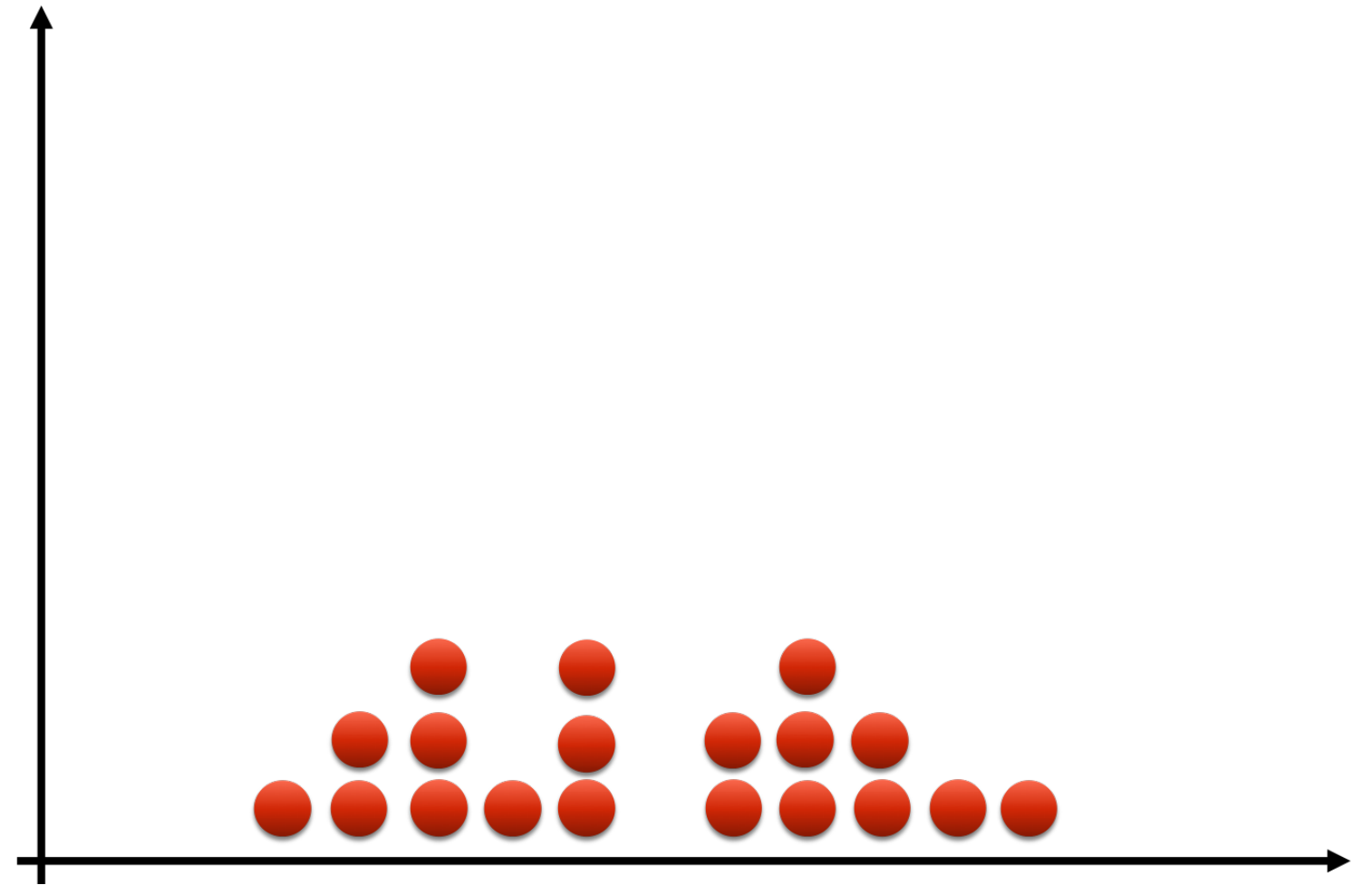
Data smoothing

- Filter: smoothen out 'bumps' of histogram
- Observations accumulate in over time



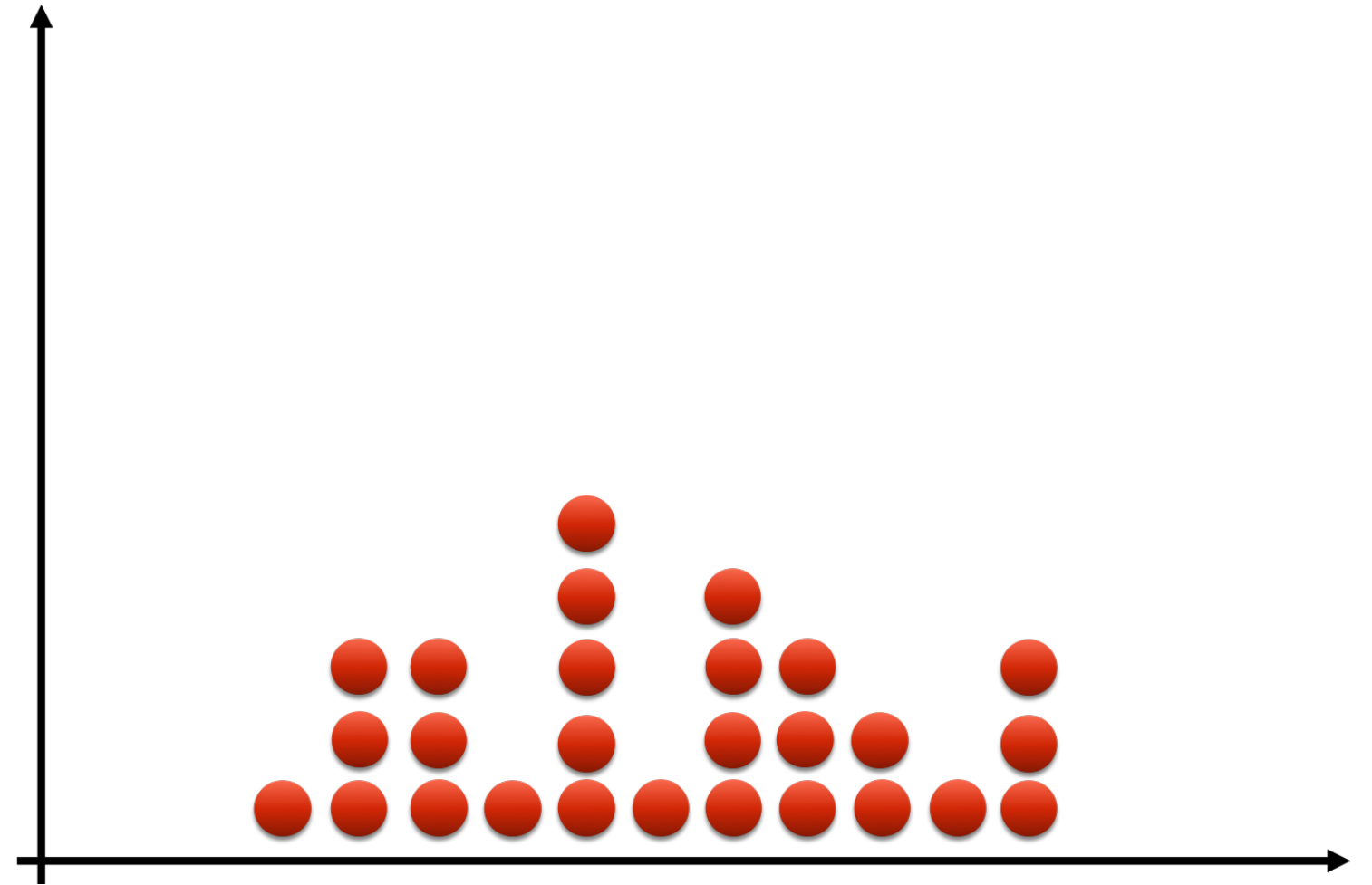
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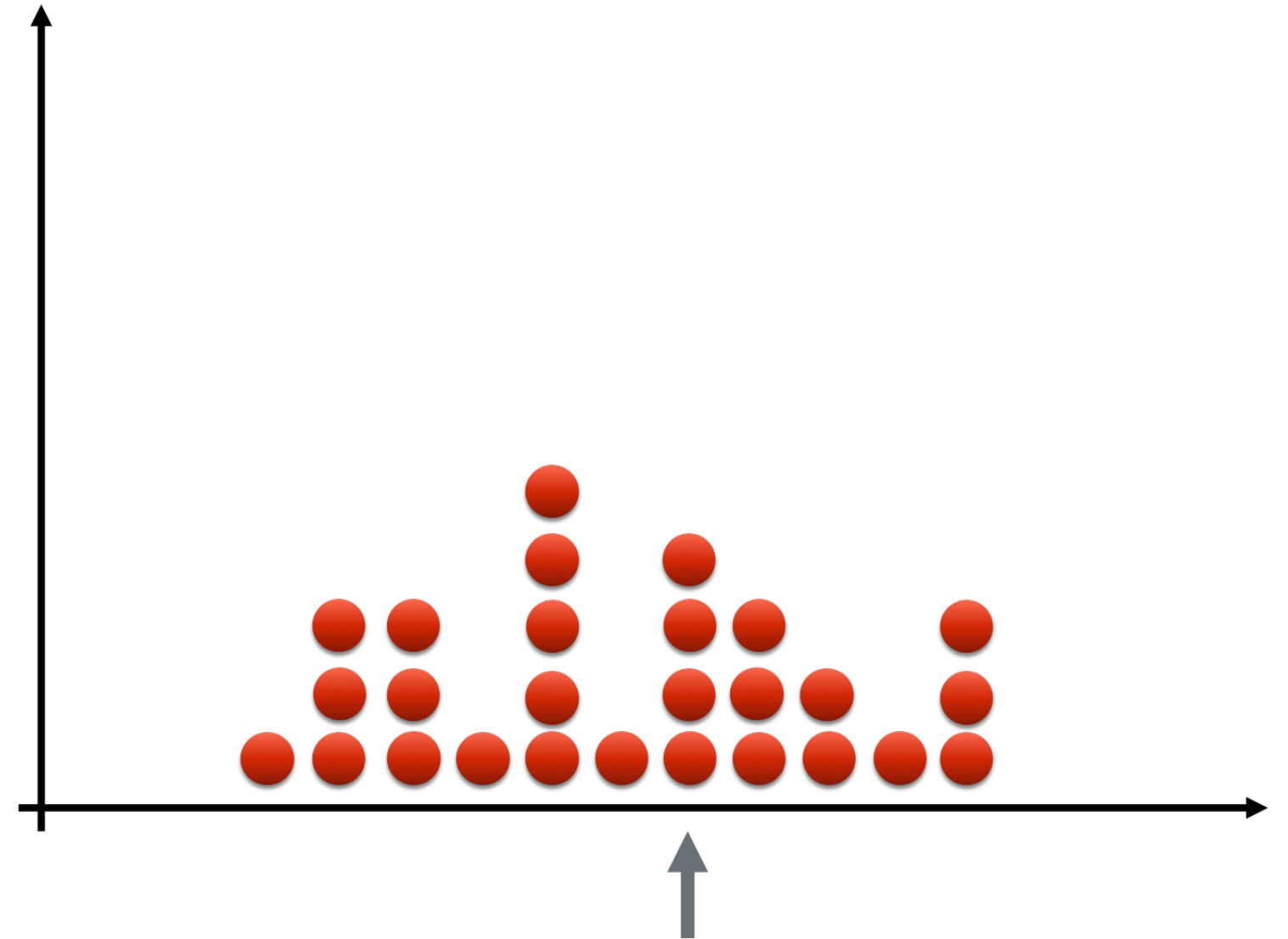
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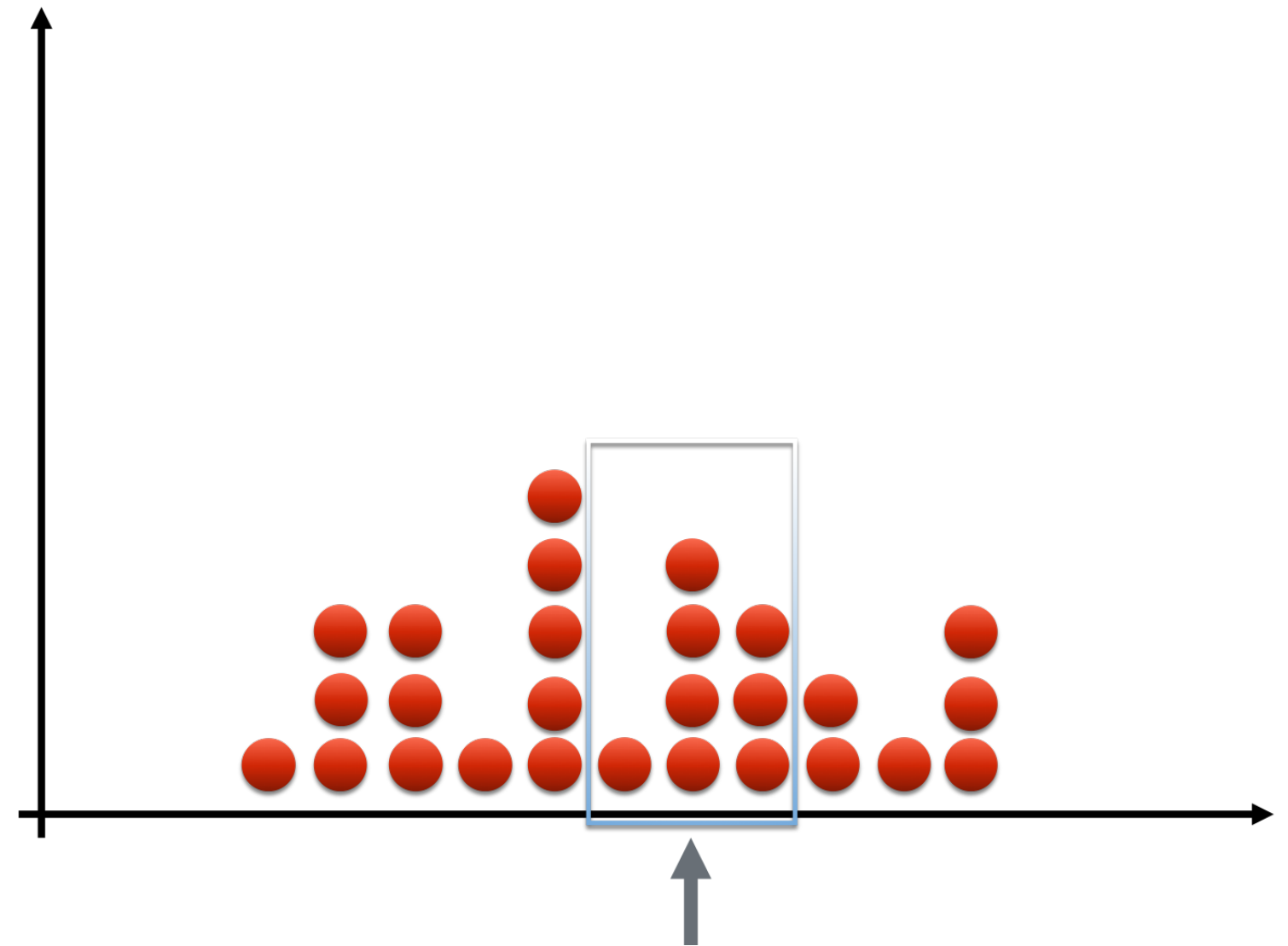
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- Observations accumulate in over time
- Pick particular portfolio loss



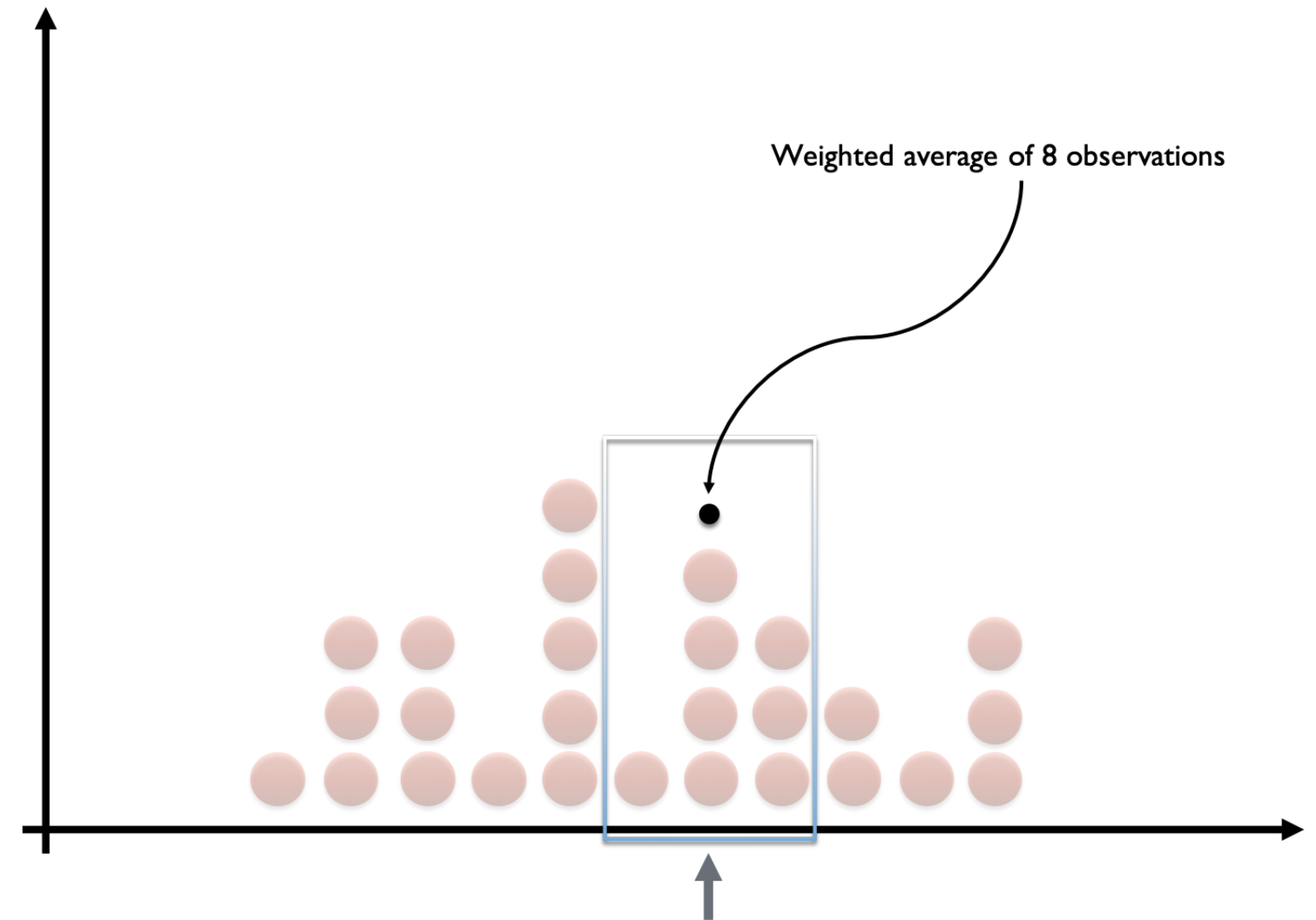
Data smoothing

- Filter: smoothen out 'bumps' of histogram
- Observations accumulate in over time
- Pick particular portfolio loss
 - Examine nearby losses



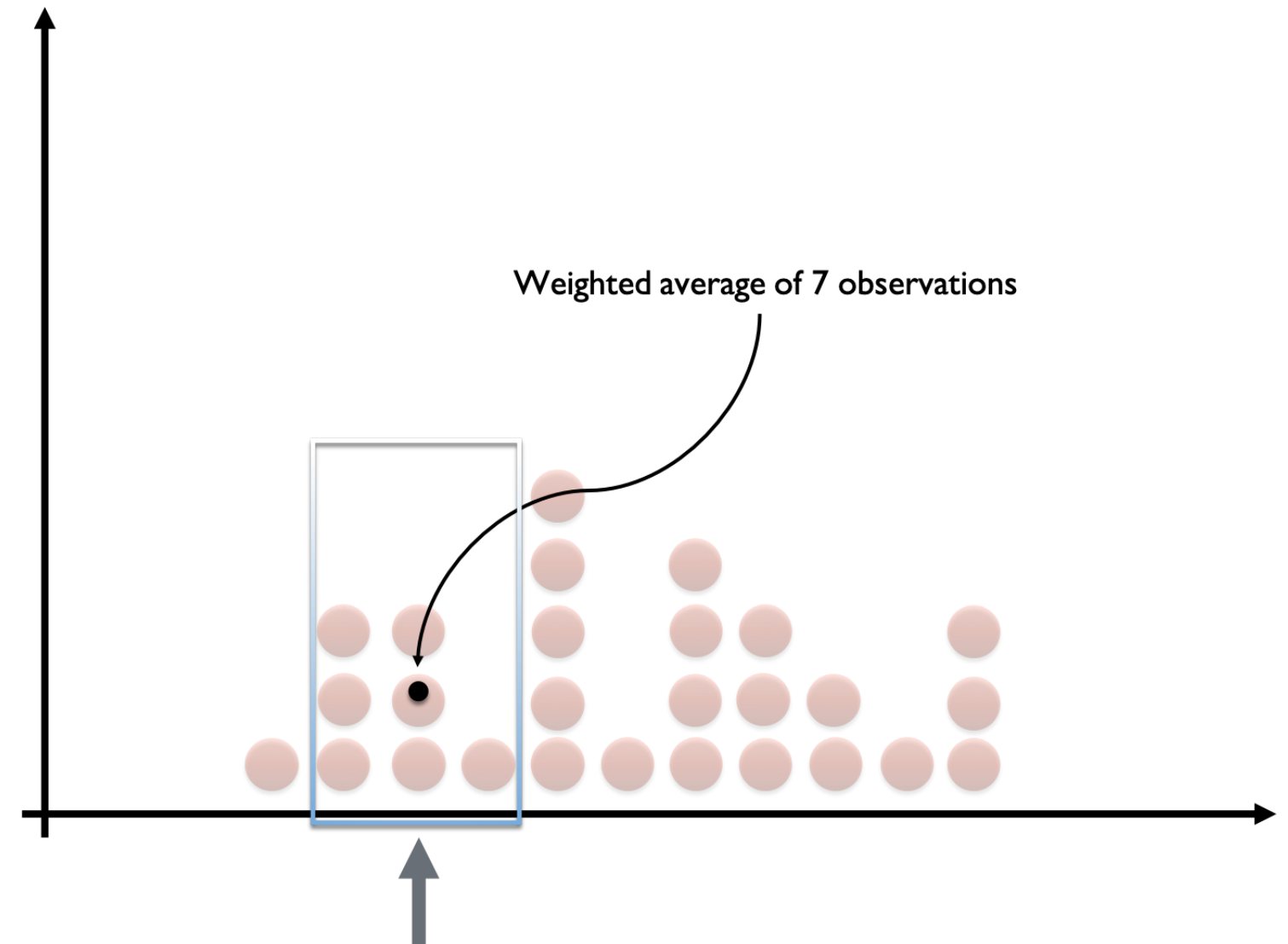
Data smoothing

- Filter: smoothen out 'bumps' of histogram
- Observations accumulate in over time
- Pick particular portfolio loss
 - Examine nearby losses
 - Form "weighted average" of losses
- **Kernel:** filter choice; determines "window"



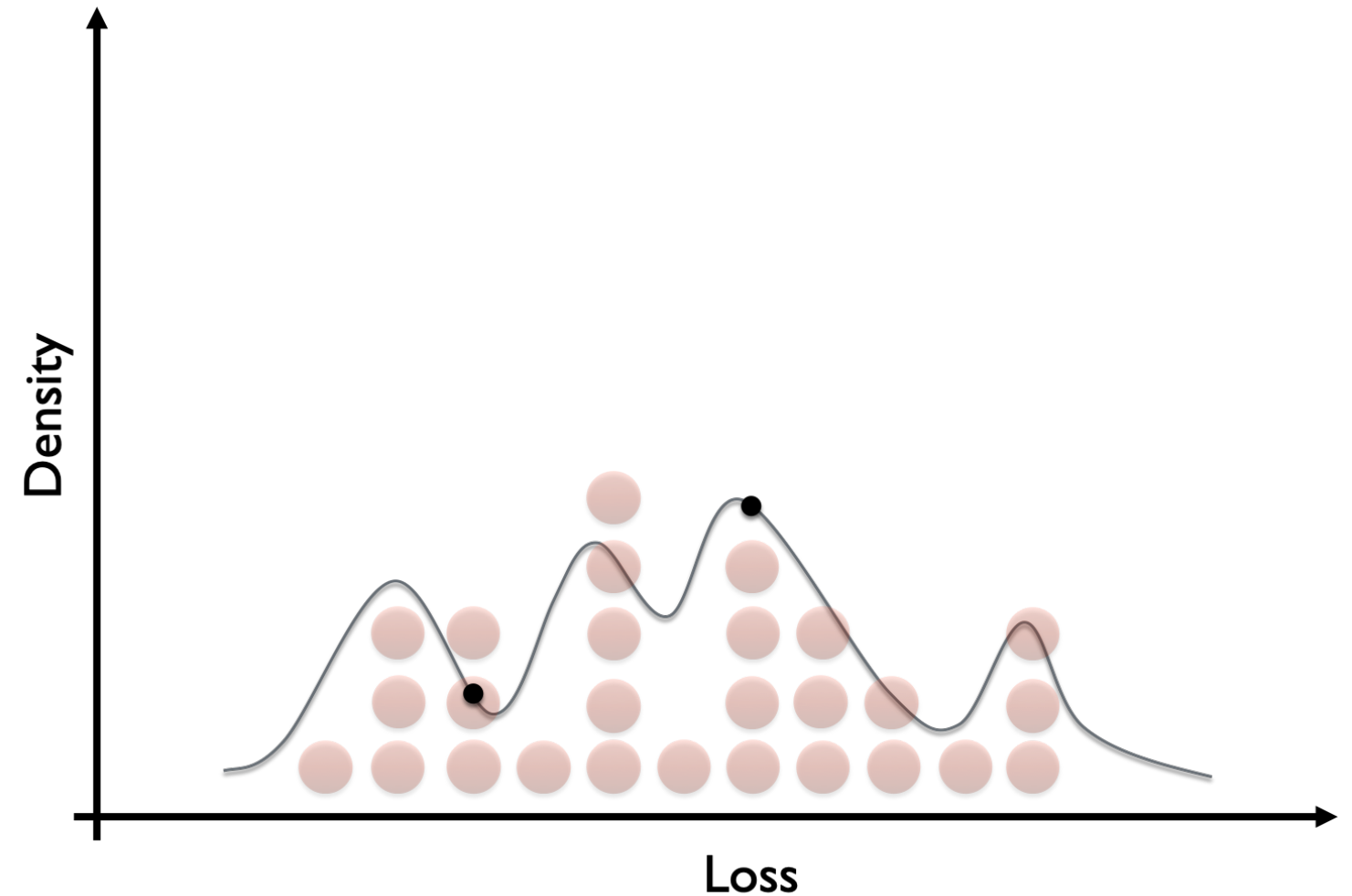
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 - Move window to another loss



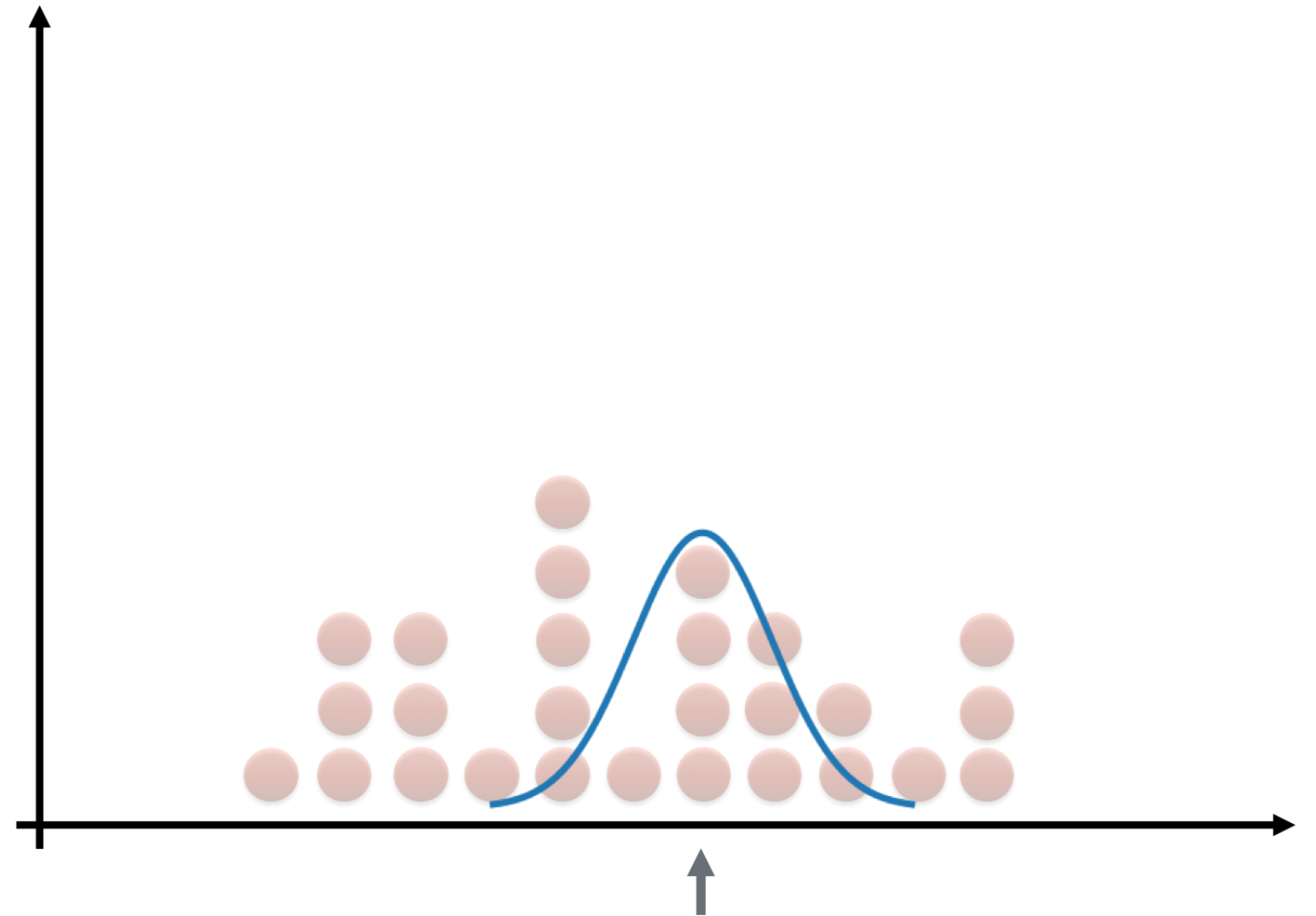
Data smoothing

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- **Kernel**: filter choice; determines "window"
 - Move window to another loss
- **Kernel density estimate**: probability density



The Gaussian kernel

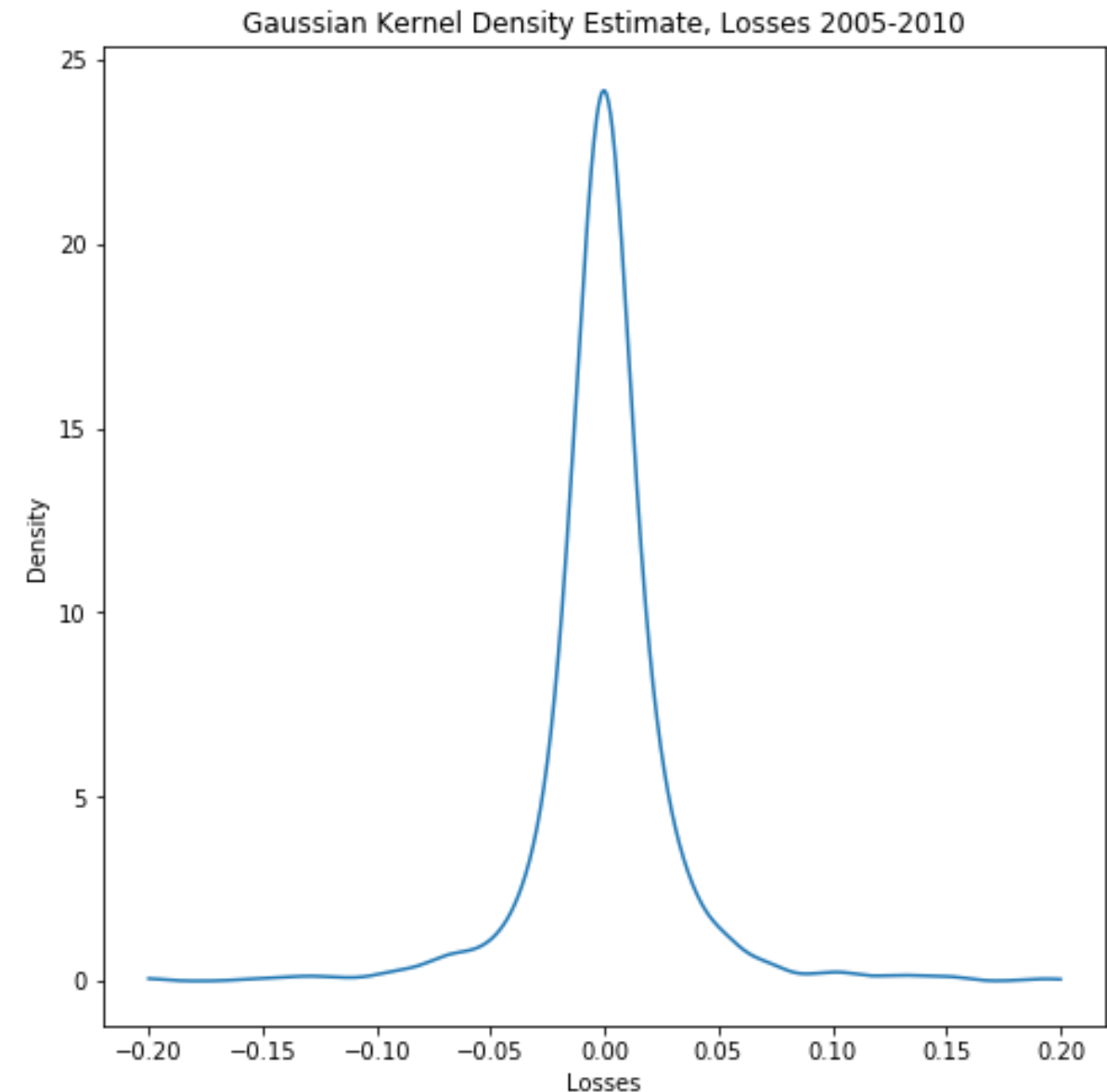
- Continuous kernel
- Weights all observations by distance from center
- **Generally:** many different kernels are available
 - Used in time series analysis
 - Used in signal processing



KDE in Python

```
from scipy.stats import gaussian_kde
kde = gaussian_kde(losses)
loss_range = np.linspace(np.min(losses),
                          np.max(losses),
                          1000)
plt.plot(loss_range, kde.pdf(loss_range))
```

- Visualization: probability density function from KDE fit



Finding VaR using KDE

- VaR: use `gaussian_kde` `.resample()` method
- Find quantile of resulting sample
- CVaR: expected value as previously encountered, but
 - `gaussian_kde` has no `.expect()` method => compute integral manually
 - special `.expect()` method written for exercise

```
sample = kde.resample(size = 1000)
VaR_99 = np.quantile(sample, 0.99)
print("VaR_99 from KDE: ", VaR_99)
```

```
VaR_99 from KDE: 0.08796423698448601
```

Let's practice!

QUANTITATIVE RISK MANAGEMENT IN PYTHON

Neural network risk management

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Real-time portfolio updating

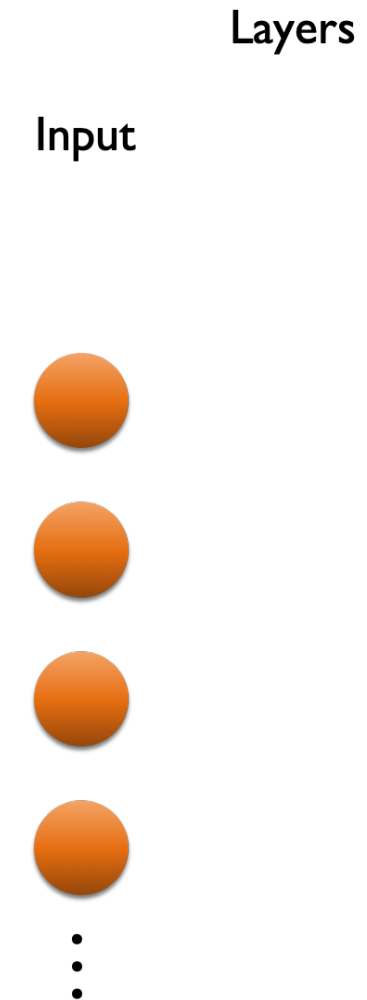
- Risk management
 - **Defined** risk measures (VaR, CVaR)
 - **Estimated** risk measures (parameteric, historical, Monte Carlo)
 - **Optimized** portfolio (e.g. Modern Portfolio Theory)
- *New* market information => *update* portfolio weights
 - **Problem:** portfolio optimization costly
 - **Solution:** $\text{weights} = f(\text{prices})$
 - *Evaluate* f in real-time
 - *Update* f only occasionally

Neural networks

- **Neural Network:** $\text{output} = f(\text{input})$
 - **Neuron:** interconnected processing node in function
- Initially developed 1940s-1950s
- **Early 2000s:** application of neural networks to "big data"
 - Image recognition, processing
 - Financial data
 - Search engine data
- **Deep Learning:** neural networks as part of Machine Learning
 - **2015:** Google releases open-source Tensorflow deep learning library for Python

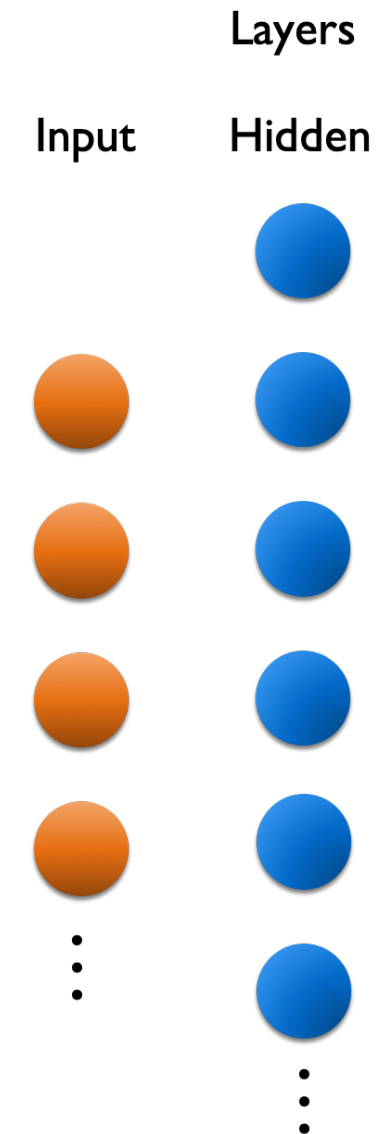
Neural network structure

- **Layers: connected processing neurons**
 - Input layer



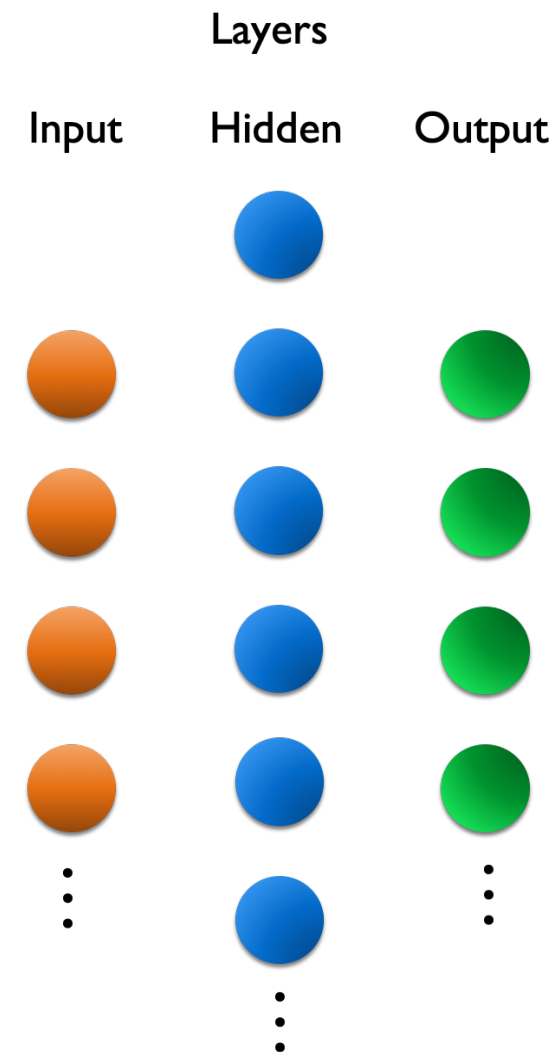
Neural network structure

- **Neural network structure**
 - Input layer
 - Hidden layer



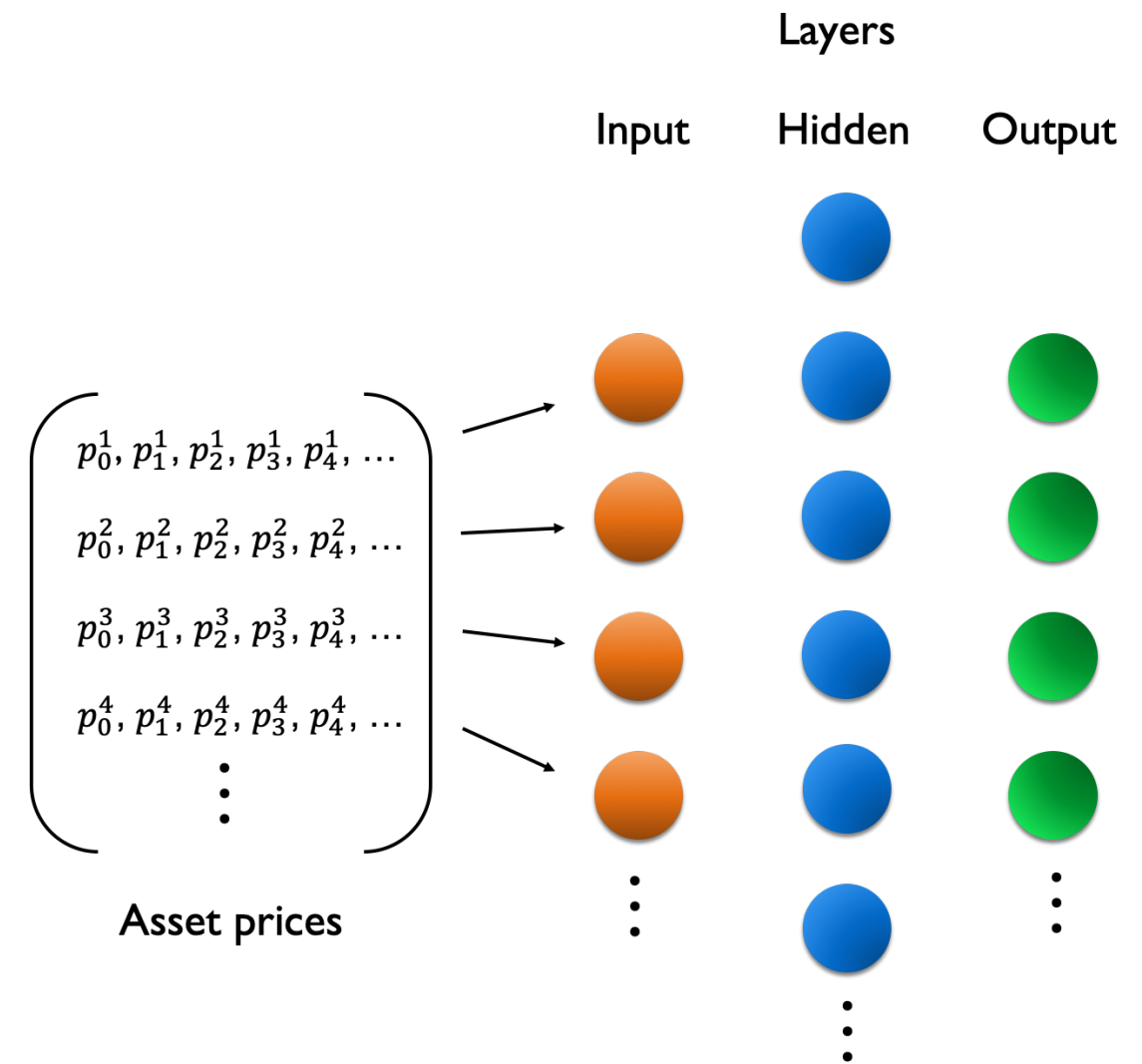
Neural network structure

- **Neural network structure**
 - Input layer
 - Hidden layer
 - Output layer
- **Training:** learn relationship between input and output



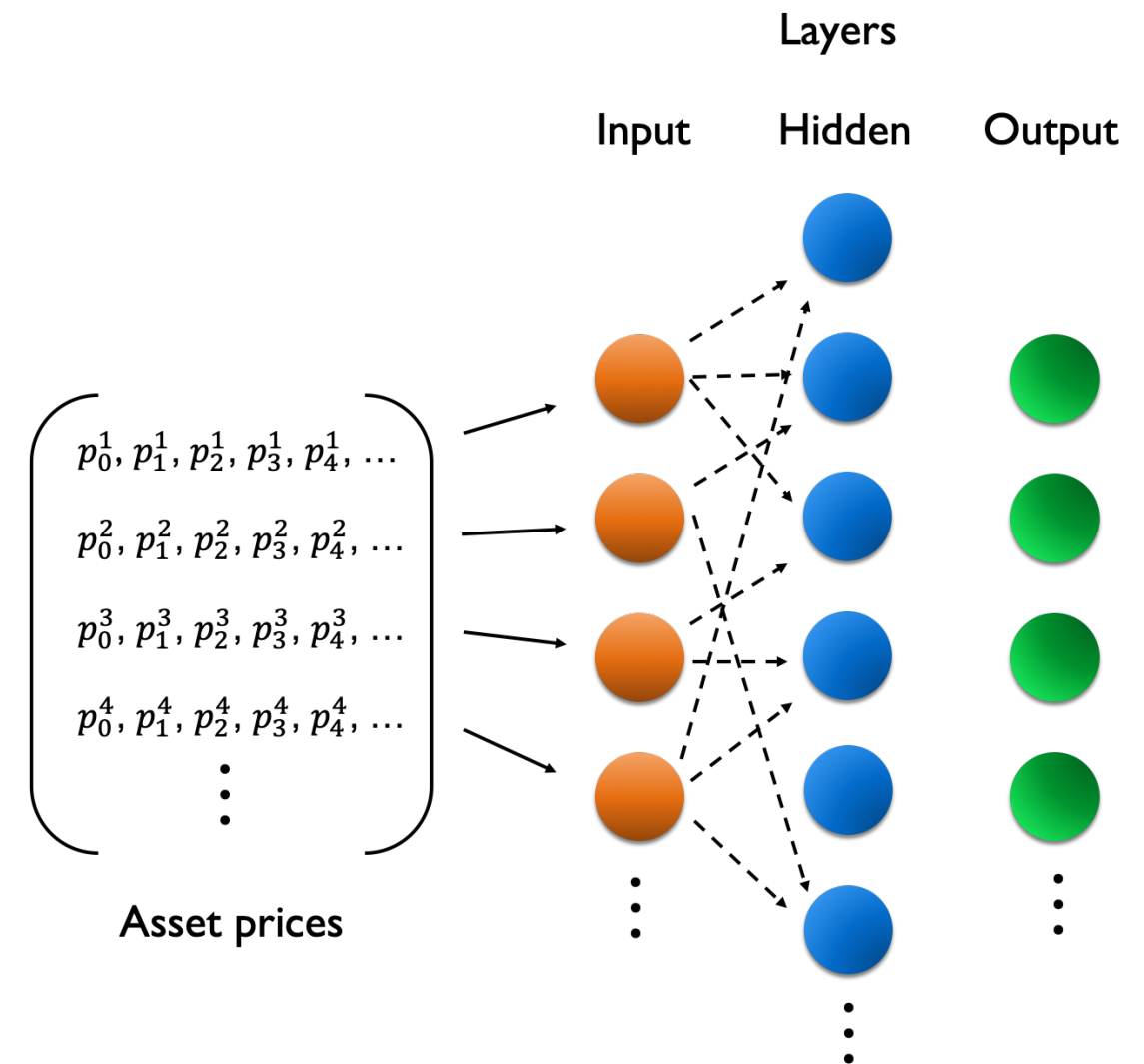
Neural network structure

- **Neural network structure**
 - Input layer
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 - Output layer
- **Training:** learn relationship between input and output
 - Asset prices => Input layer



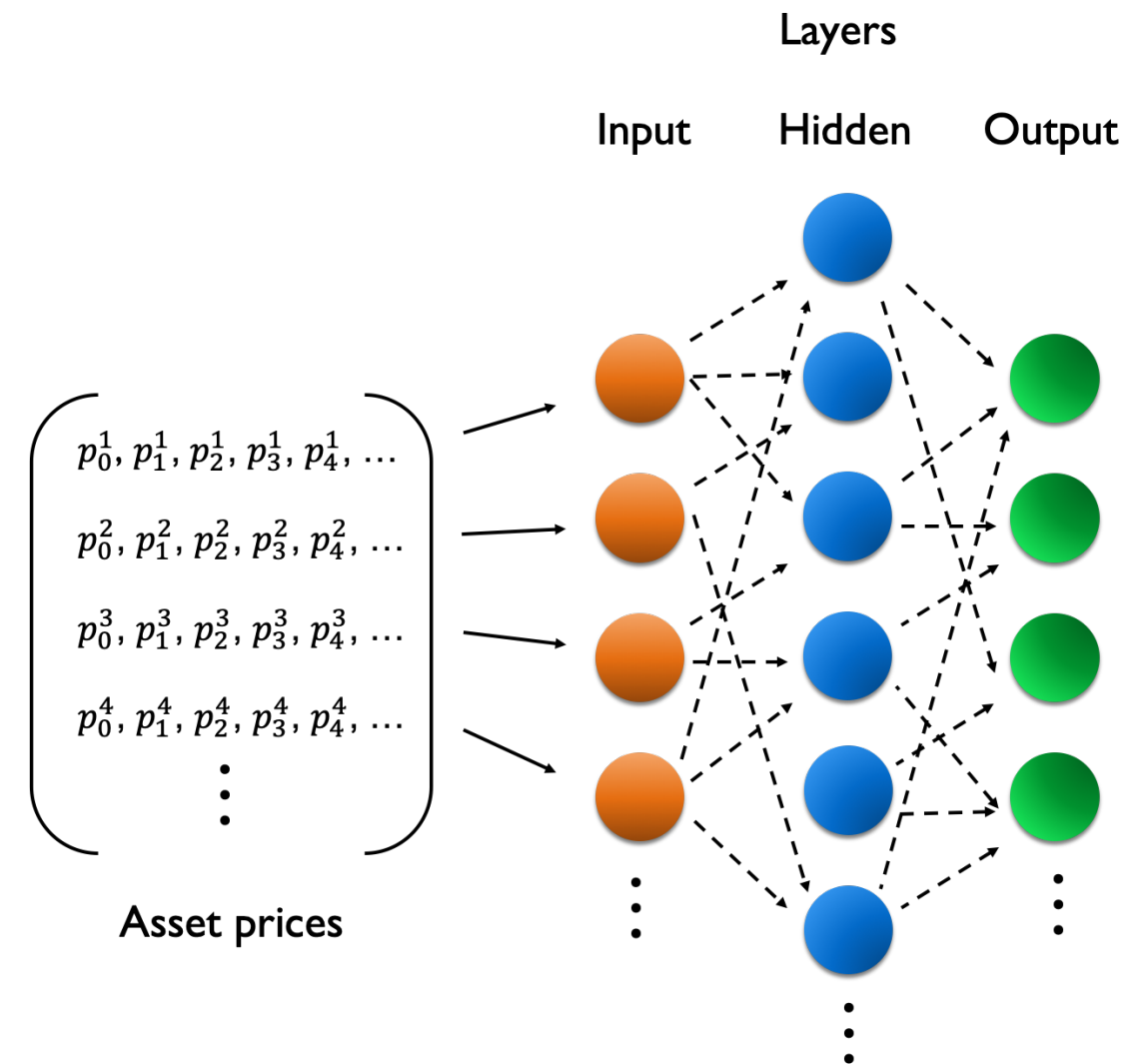
Neural network structure

- **Neural network structure**
 - Input layer
 - Hidden layer
 - Output layer
- **Training:** learn relationship between input and output
 - Asset prices => Input layer
 - Input + hidden layer processing



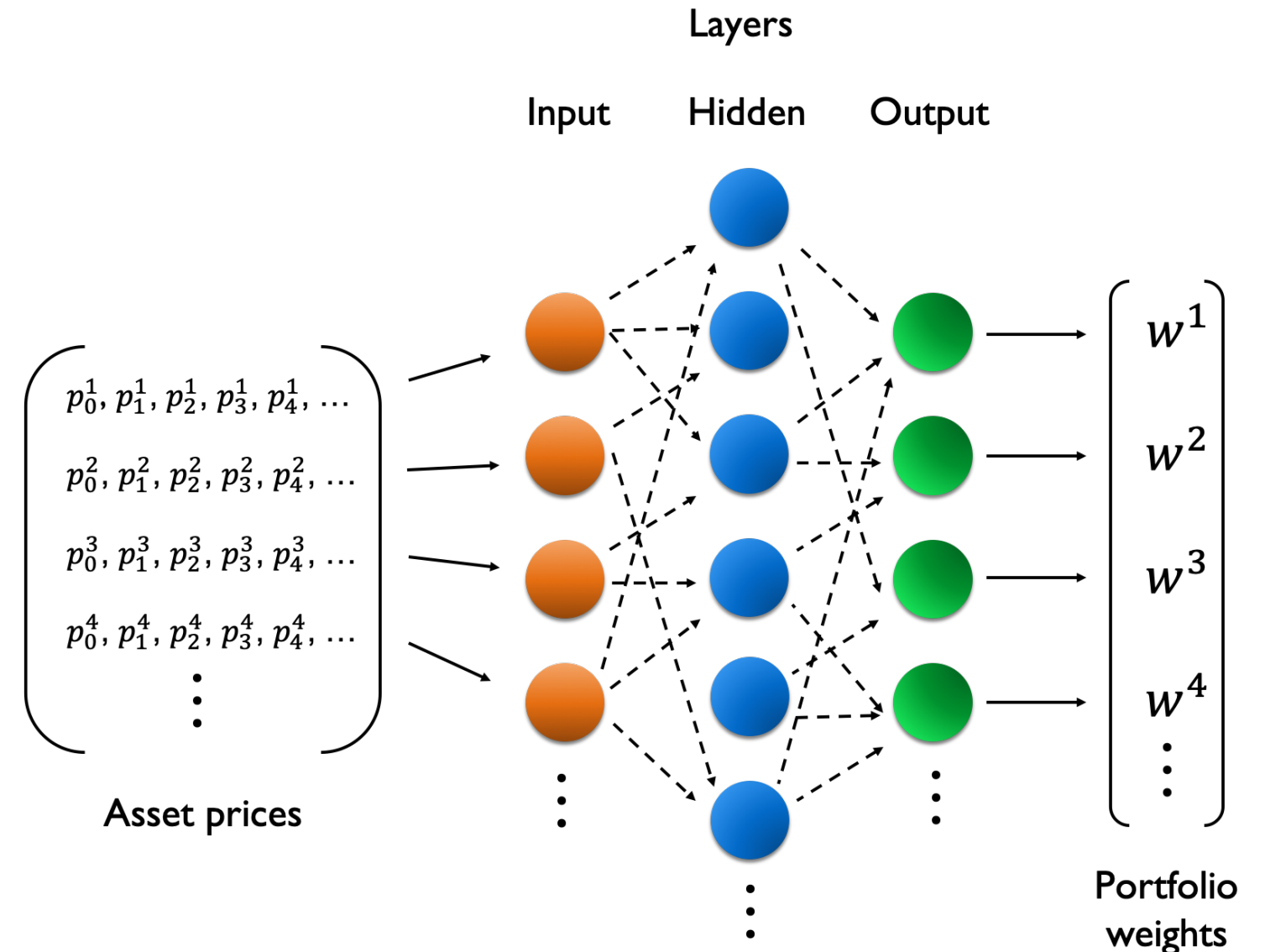
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Neural network structure

- **Neural network structure**
 - Input layer
 - Hidden layer
 - Output layer
- **Training:** learn relationship between input and output
 - Asset prices => Input layer
 - Input + hidden layer processing
 - Hidden + output layer processing
 - Output => portfolio weights



Using neural networks for portfolio optimization

- **Training**

- *Compare* output and pre-existing "best" portfolio weights
- **Goal:** minimize "error" between output and weights
- Small error => network is *trained*

- **Usage**

- **Input:** new, unseen asset prices
- **Output:** predicted "best" portfolio weights for new asset prices
- Best weights = risk management

Creating neural networks in Python

- **Keras:** high-level Python library for neural networks/deep learning
- Further info: [Introduction to Deep Learning with Keras](#)

```
from keras.models import Sequential
from keras.layers import Dense
model = Sequential()
model.add(Dense(10, input_dim=4, activation='sigmoid'))
model.add(Dense(4))
```

Training the network in Python

- Historical asset prices: `training_input` matrix
- Historical portfolio weights: `training_output` vector
- **Compile** model with:
 - given error minimization ('**loss**')
 - given optimization algorithm ('**optimizer**')
- **Fit** model to training data
 - **epochs**: number of training loops to update internal parameters

```
model.compile(loss='mean_squared_error', optimizer='rmsprop')  
model.fit(training_input, training_output, epochs=100)
```

Risk management in Python

- **Usage:** provide new (e.g. real-time) asset pricing data
 - **New vector** `new_asset_prices` given to input layer
- Evaluate network using `model.predict()` on new prices
 - **Result:** `predicted` portfolio weights
- Accumulate enough data over time => **re-train** network
 - Test network on previous data => **backtesting**

```
# new asset prices are in the vector new_asset_prices
predicted = model.predict(new_asset_prices)
```


Let's practice!

QUANTITATIVE RISK MANAGEMENT IN PYTHON

Wrap-up and Future Steps

QUANTITATIVE RISK MANAGEMENT IN PYTHON



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Congratulations!

Chapter I

Risk and
Return Recap

Return Distribution

Risk Factors

Volatility & Covariance

Modern Portfolio Theory

Efficient Portfolio &
Efficient Frontier

Congratulations!

Chapter 1

Risk and
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Chapter 2

Goal-oriented Risk
Management

Loss Distribution

Value at Risk (VaR)

Conditional VaR

Risk Exposure

Portfolio Hedging

Congratulations!

| Chapter 1 | Chapter 2 | Chapter 3 |
|--|-------------------------------|-------------------------------|
| Risk and Return Recap | Goal-oriented Risk Management | Estimating & Identifying Risk |
| Return Distribution | Loss Distribution | Parametric Estimation |
| Risk Factors | Value at Risk (VaR) | Historical Simulation |
| Volatility & Covariance | Conditional VaR | Monte Carlo Simulation |
| Modern Portfolio Theory | Risk Exposure | Structural Breaks |
| Efficient Portfolio & Efficient Frontier | Portfolio Hedging | Extreme Events |

Congratulations!

| Chapter 1 | Chapter 2 | Chapter 3 | Chapter 4 |
|--|-------------------------------|-------------------------------|---------------------------|
| Risk and Return Recap | Goal-oriented Risk Management | Estimating & Identifying Risk | Advanced Risk Management |
| Return Distribution | Loss Distribution | Parametric Estimation | Extreme Value Theory |
| Risk Factors | Value at Risk (VaR) | Historical Simulation | Kernel Density Estimation |
| Volatility & Covariance | Conditional VaR | Monte Carlo Simulation | Neural Networks |
| Modern Portfolio Theory | Risk Exposure | Structural Breaks | Real-time risk management |
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Tools in your toolkit

| Scipy | Statsmodels | PyPortfolioOpt | Keras |
|-----------------------------|------------------------------|---------------------------------------|---------------------------|
| <code>scipy.stats</code> | <code>statsmodels.api</code> | <code>pypfopt</code> | <code>keras</code> |
| <code>norm()</code> | <code>OLS()</code> | <code>risk_models</code> | <code>models</code> |
| <code>skewnorm()</code> | <code>add_constant()</code> | <code>cla</code> | <code>layers</code> |
| <code>t()</code> | <code>.fit()</code> | <code>expected_returns</code> | <code>Sequential()</code> |
| <code>genextreme()</code> | | <code>efficient_frontier</code> | <code>Dense()</code> |
| <code>gaussian_kde()</code> | | <code>objective_functions</code> | <code>.add()</code> |
| <code>anderson()</code> | | <code>EfficientFrontier()</code> | <code>.fit()</code> |
| <code>skewtest()</code> | | <code>mean_historical_return()</code> | <code>.predict()</code> |
| <code>.pdf()</code> | | <code>CovarianceShrinkage()</code> | |
| <code>.ppf()</code> | | <code>.negative_cvar()</code> | |
| <code>.fit()</code> | | <code>.CLA()</code> | |
| <code>.rvs()</code> | | <code>.ledoit_wolf()</code> | |

Future steps and reference

- **Upcoming DataCamp courses**
 - Credit Risk Modeling in Python
 - Financial Forecasting in Python
 - Machine Learning for Finance in Python
 - GARCH Models for Finance in Python
- *Quantitative Risk Management: Concepts, Techniques and Tools*, McNeil, Frey & Embrechts, Princeton UP, 2015.

**Best of luck on your
data science
journey!**

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