



# Machine Learning for Time Series Exercise

Richard Dirauf, M.Sc.

Machine Learning and Data Analytics (MaD) Lab

Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU)

MLTS Exercise, 03.11.2022

---

Fridays, 12:15-13:45 via [Zoom](#)

Recordings of last years exercises uploaded to [FAU TV](#)

Five topics with two exercise sessions each:

- Session 1: Recap of topic and introduction of coding task
- Session 2: Solution to coding task and questions

Recommended: solve coding task as homework

Slides and tasks uploaded on [StudOn](#)

Questions: Exercises or [Forum](#)



What is your major?

Python experience?

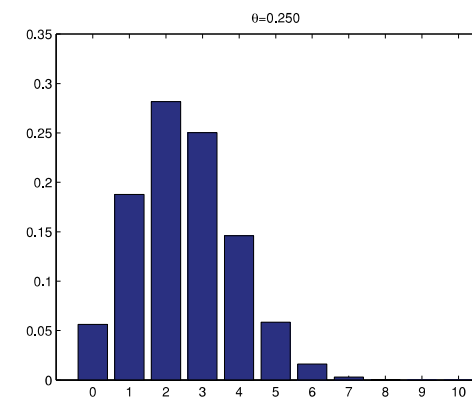


# MLTS Exercises

## Basics

- Discrete

probability mass function (pmf)



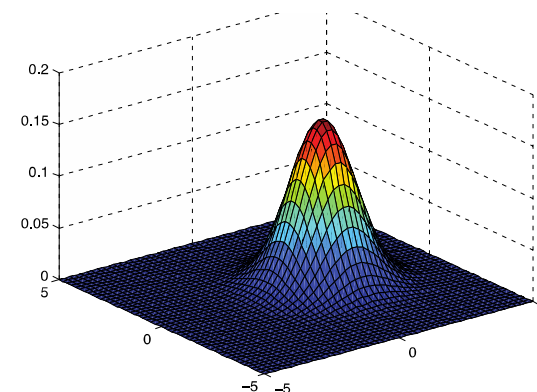
Binomial distribution

- Continuous

probability density function (pdf)

$$0 \leq p(x) \leq 1$$

$$\int_{-\infty}^{+\infty} p(x) dx = 1$$



Gaussian (normal) distribution

## Mean or expected value of a distribution

Discrete distribution

$$\mathbb{E}[X] \triangleq \sum_{x \in \mathcal{X}} x p(x)$$

Continuous distribution

$$\mathbb{E}[X] \triangleq \int_{\mathcal{X}} x p(x) dx$$

The expected value of function  $f$

Discrete distribution

$$\mathbb{E}[f] \triangleq \sum_{x \in \mathcal{X}} f(x) p(x)$$

Continuous distribution

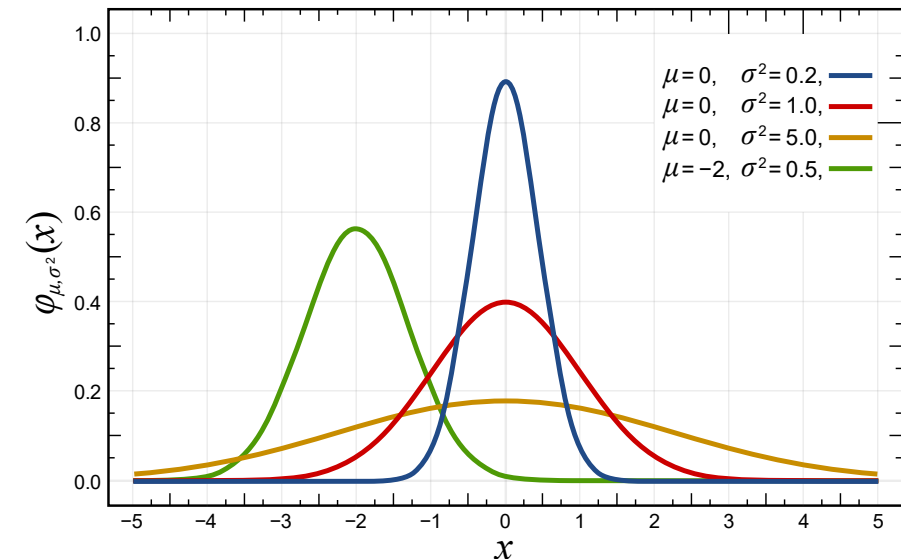
$$\mathbb{E}[f] \triangleq \int_{\mathcal{X}} f(x) p(x) dx$$

The **variance** is a measure of the spread of a distribution

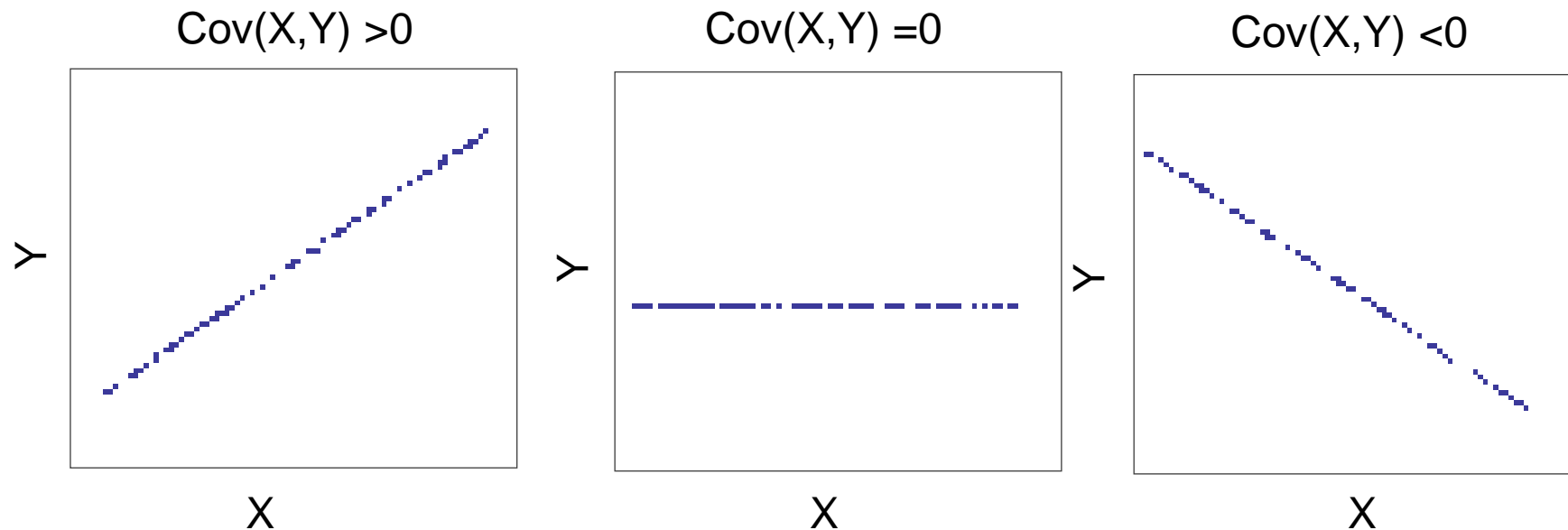
$$\begin{aligned}\text{var}[X] &\triangleq \mathbb{E}[(X - \mu)^2] = \int (x - \mu)^2 p(x) dx \\ &= \int x^2 p(x) dx + \mu^2 \int p(x) dx - 2\mu \int x p(x) dx = \mathbb{E}[X^2] - \mu^2\end{aligned}$$

The standard deviation is defined as

$$\text{std}[X] \triangleq \sqrt{\text{var}[X]}$$



$$\text{cov}[X, Y] \triangleq \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$$





- Probability of the **joint distribution** X and Y as follows

$$p(X, Y) = p(X|Y)p(Y)$$

this is sometimes called the **product rule**.

- We define the **marginal distribution** as follows

$$p(X) = \sum_y p(X, Y) = \sum_y p(X|Y = y)p(Y = y)$$

where we are summing over all possible states of Y.

This is sometimes called the **sum rule**.

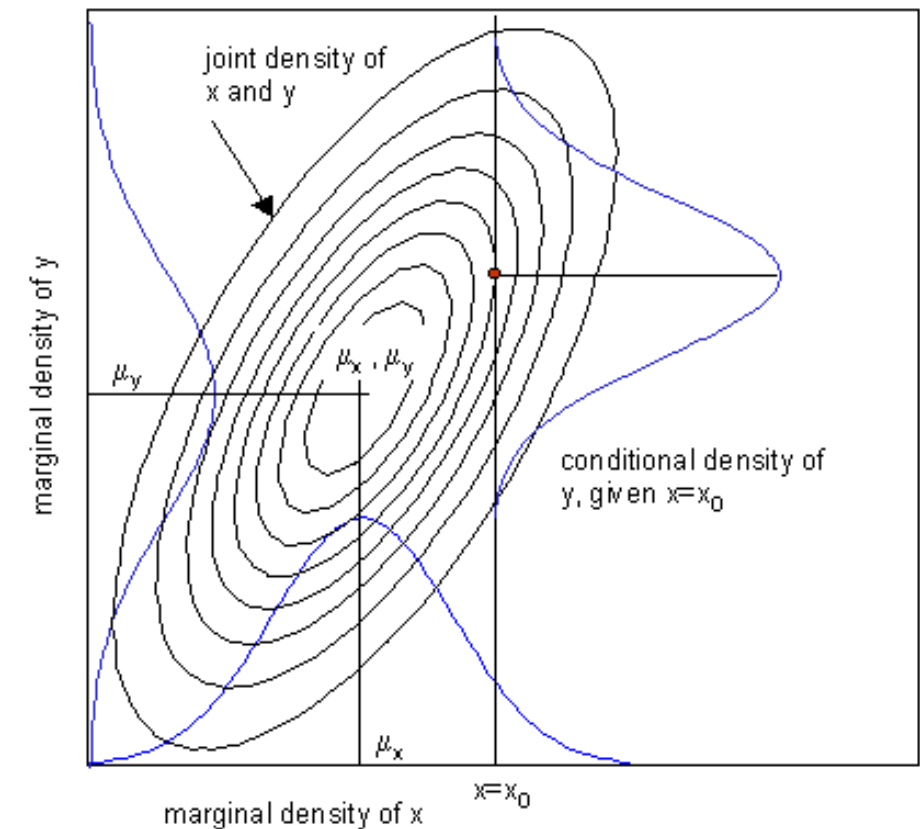
- The product rule can be applied multiple times to yield the chain rule of probability:

$$p(X_{1:D}) = p(X_1)p(X_2|X_1)p(X_3|X_2, X_1)p(X_4|X_1, X_2, X_3) \dots p(X_D|X_{1:D-1})$$

## Concepts of joint, marginal, and conditional probabilities

$$x \sim \mathcal{N}(\mu_x, \sigma_x^2)$$

$$y \sim \mathcal{N}(\mu_y, \sigma_y^2)$$



Posterior probability

$$p(X = x | Y = y)$$

$$= \frac{p(X = x, Y = y)}{p(Y = y)}$$

Prior probability

$$p(X = x)$$

Likelihood

$$p(Y = y | X = x)$$

$$\sum_{x'} p(X = x') p(Y = y | X = x')$$

Marginal likelihood



# Thank you for your attention!

## Any questions?