LES FACULTÉS
DE L'UNIVERSITÉ
CATHOLIQUE DE LILLE

Inference & Estimation theory

BAYESIAN INFERENCES

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KNOWLEDGE TREE

Part 1: Foundations of Bayesian Thinking

1.1 Introduction to Bayesian Philosophy

- Historical context and the Bayesian vs. Frequentist debate
- The subjective nature of Bayesian probability

1.2 Basics of Conditional Probability

- The conditional probability formula
- Independent and dependent events

1.3 Bayes' Theorem

- Derivation and importance
- Real-world applications and examples

1.4 Prior, Likelihood, and Posterior

- Definitions and their roles in Bayesian analysis
- The concept of updating beliefs

1.3 Bayesian Statistics Distributions:

- Beta distribution
- Dirichlet distribution

Part 2: Bayesian Inference and Estimation

2.1 Bayesian Parameter Estimation

- Point estimation using posterior mean, median, and mode
- Credible intervals as Bayesian analogs to confidence intervals

2.2 Conjugate Priors

- Introduction and benefits
- Examples with common distributions (e.g., Beta-Binomial, Normal-Normal)

2.3 Hierarchical and Empirical Bayes

- Multi-level modeling with hierarchical Bayes
- Shrinking estimates with empirical Bayes

2.4 Bayesian Model Selection

- Bayesian information criteria (BIC) and other metrics
- Bayesian model averaging

Part 3: Computational Methods in Bayesian Analysis

3.1 Markov Chain Monte Carlo (MCMC)

- Introduction to MCMC and its importance
- Metropolis-Hastings, Gibbs sampling, and other algorithms

3.2 Hamiltonian Monte Carlo and NUTS

- Advanced MCMC methods for complex models
- Benefits and challenges

3.3 Approximate Bayesian Computation (ABC)

- When likelihood is intractable
- ABC principles and applications

3.4 Variational Inference

- Introduction and contrast with MCMC
- Use cases and limitations

Part 4: Applications and Challenges

4.1 Bayesian Networks and Graphical Models

- Conditional dependencies and d-separation
- Inference in Bayesian networks

4.2 Real-World Applications of Bayesian Methods

- Examples from different fields in biology
- Case studies

4.3 Priors and Subjectivity

- Objective vs. subjective priors
- Critiques and considerations

4.4 Challenges and Frontiers

- Computational challenges in high-dimensional spaces
- Future directions in Bayesian analysis and emerging trends

KEYWORDS (NEW)

Condition · Vérification bayésienne · Théorème de l'espérance conditionnelle · Théorie de la décision bayésienne · Régression bayésienne · Prior · Conjugate Prior

Variance conditionnelle · Table de probabilité conditionnelle (TPC) · Théorème de Bayes-Laplace · Distribution a priori · Modèle bayésien · Bayes profond

Théorème de Bayes · Inférence bayésienne par Monte Carlo (MCMC) · Statistique bayésienne empirique · Espérance conditionnelle · Prédiction bayésienne · Classifieur bayésien

Statistiques bayésiennes · Chaîne de Markov Monte Carlo (MCMC) · Estimation des paramètres bayésiens · Évidence (Evidence) · Probabilité conjointe · Probabilité subjective

Probabilités conditionnelles · Approche bayésienne de la régression logistique · Fonction de densité a posteriori · Inférence bayésienne · Probabilité marginale · Probabilité totale

Fonction de densité a priori · Analyse de sensibilité bayésienne · Fusion de données bayésiennes · Inférence statistique · Critère d'information d'Aikaike (AIC)

Intervalle de crédibilité · Approximation bayésienne · Convergence bayésienne · Intervalle de prévision · Bayes factor (Facteur bayésien)

Loi a priori non informative · Analyse de Bayes en survie · Critère d'information bayésien (BIC) · Intervalles de prédiction · Loi a priori informative · Distribution a posteriori

Méthode de Bayes · Loi conditionnelle · Algorithme de Monte Carlo par chaîne de Markov (MCMC) · Probabilité conditionnelle · Algorithme de Metropolis-Hastings

Croyance bayésienne · Classification bayésienne · Bayésien itératif (IBE) · Bayes en réseau neuronal

KEYWORDS

- Foundations of Bayesian Thinking
- Bayesian Philosophy
- Bayesian Probability
- Probabilistic Inference
- Data Scientist
- Researcher
- Bayesianism
- Bayesian versus Frequentist
- Subjective Probability
- Conditional Probability
- Independent Events
- Dependent Events
- Bayes' Theorem
- Prior Probability
- Likelihood
- Posterior Probability
- Parameter Estimation
- Posterior Mean
- Posterior Median
- Posterior Mode
- Credible Intervals
- Conjugate Priors
- Beta-Binomial Distribution
- Normal-Normal Distribution
- Hierarchical Bayes
- Empirical Bayes
- Multi-Level Modeling
- Bayesian Model Selection
- Bayesian Information Criteria (BIC)
- Bayesian Model Averaging
- Computational Methods
- Markov Chain Monte Carlo (MCMC)
- Metropolis-Hastings Algorithm
- Gibbs Sampling
- Hamiltonian Monte Carlo
- No-U-Turn Sampler (NUTS)
- Approximate Bayesian Computation (ABC)
- Variational Inference
- Bayesian Networks
- Graphical Models
- Conditional Dependencies
- d-Separation
- Objective Priors
- Subjective Priors
- Bayesian Applications
- Bayesian Challenges
- Computational Challenges
- High-Dimensional Spaces
- Bayesian Frontiers
- Emerging Trends
- Bayesian Analysis

Use Case with python

Use Case: Bayesian Analysis in Healthcare Decision-Making

In the context of the course on Bayesian Thinking, covering topics on Bayesian philosophy, inference, computational methods, and real-world applications, let's explore a use case related to using Bayesian analysis for healthcare decision-making. This use case involves applying Bayesian methods to assess the effectiveness of a new medical treatment.

Description:

In this use case, we will focus on using Bayesian analysis to make informed decisions about the efficacy of a new medical treatment. We will apply Bayesian philosophy, conditional probability, Bayes' theorem, parameter estimation, and computational methods to evaluate the treatment's effectiveness based on clinical trial data.

Key Components:

Foundations of Bayesian Thinking: Understanding the Bayesian philosophy, conditional probability, Bayes' theorem, and the role of prior, likelihood, and posterior in Bayesian analysis.

Bayesian Inference and Estimation: Performing Bayesian parameter estimation, calculating credible intervals, and exploring the concept of conjugate priors.

Computational Methods in Bayesian Analysis: Implementing Markov Chain Monte Carlo (MCMC) methods, including Metropolis-Hastings and Gibbs sampling, to analyze complex medical data.

Applications and Challenges: Applying Bayesian analysis to healthcare data, considering the subjective nature of priors, and addressing computational challenges in high-dimensional spaces.

Python Code Example (Bayesian Analysis for Medical Treatment):

```python
import numpy as np
import pymc3 as pm
import matplotlib.pyplot as plt

# Generate synthetic clinical trial data (treatment vs. control)
np.random.seed(42)
control_group = np.random.normal(70, 10, size=50)
treatment_group = np.random.normal(75, 12, size=50)

# Bayesian analysis using PyMC3
with pm.Model() as medical_treatment_model:
    # Priors
    treatment_effect = pm.Normal('treatment_effect', mu=0, sigma=20)

    # Likelihood
    control_group_likelihood = pm.Normal('control_group_likelihood',
    mu=control_group, sigma=10, observed=control_group)
    treatment_group_likelihood = pm.Normal('treatment_group_likelihood',
    mu=control_group + treatment_effect, sigma=12,
    observed=treatment_group)

    # Posterior estimation
    trace = pm.sample(1000, tune=1000)

# Bayesian parameter estimation
posterior_mean = np.mean(trace['treatment_effect'])
credible_interval = pm.hpd(trace['treatment_effect'])

# Plot posterior distribution
pm.plot_posterior(trace, var_names=['treatment_effect'],
credible_interval=0.95)
plt.xlabel('Treatment Effect')
plt.ylabel('Posterior Density')
plt.title('Bayesian Analysis of Treatment Effect')
plt.show()

print(f'Posterior Mean Treatment Effect: {posterior_mean:.2f}')
print(f'95% Credible Interval: {credible_interval[0]:.2f} to
{credible_interval[1]:.2f}')
```

In this code, we use synthetic clinical trial data for both control and treatment groups. We apply Bayesian analysis with PyMC3 to estimate the treatment effect and calculate a credible interval to assess the effectiveness of the medical treatment.

This use case illustrates how Bayesian analysis can be applied to healthcare decision-making, providing a probabilistic framework for evaluating the impact of medical treatments and making informed choices in the field of healthcare.

REFERENCES V2

TOP 20 REFERENCES

- Gelman, A., Carlin, J. B., Stern, H. S., & Rubin, D. B. (2014). Bayesian Data Analysis. CRC Press.
- Murphy, K. P. (2012). Machine Learning: A Probabilistic Perspective. MIT Press.
- Robert, C., & Casella, G. (2004). Monte Carlo Statistical Methods. Springer.
- Jaynes, E. T. (2003). Probability Theory: The Logic of Science. Cambridge University Press.
- Efron, B. (2012). Bayesian Inference and the Parametric Bootstrap. The Annals of Applied Statistics.
- Bernardo, J. M., & Smith, A. F. (2009). Bayesian Theory. Wiley.
- Koller, D., & Friedman, N. (2009). Probabilistic Graphical Models: Principles and Techniques. MIT Press.
- Spiegelhalter, D., Abrams, K., & Myles, J. (2004). Bayesian Approaches to Clinical Trials and Health-Care Evaluation. Wiley.
- Kruschke, J. K. (2014). Doing Bayesian Data Analysis: A Tutorial with R, JAGS, and Stan. Academic Press.
- Wasserman, L. (2004). All of Statistics: A Concise Course in Statistical Inference. Springer.
- Andrieu, C., De Freitas, N., Doucet, A., & Jordan, M. I. (2003). An Introduction to MCMC for Machine Learning. Machine Learning.
- Brooks, S., Gelman, A., Jones, G., & Meng, X.-L. (2011). Handbook of Markov Chain Monte Carlo. CRC Press.
- MacKay, D. J. C. (2003). Information Theory, Inference, and Learning Algorithms. Cambridge University Press.
- Lee, P. M. (2012). Bayesian Statistics: An Introduction. Wiley.
- Betancourt, M. (2017). A Conceptual Introduction to Hamiltonian Monte Carlo. arXiv preprint.
- Beaumont, M. A. (2010). Approximate Bayesian Computation in Evolution and Ecology. Annual Review of Ecology, Evolution, and Systematics.
- Bishop, C. M. (2006). Pattern Recognition and Machine Learning. Springer.
- Ghahramani, Z. (2015). Probabilistic Machine Learning and Artificial Intelligence. Nature.
- Hoff, P. D. (2009). A First Course in Bayesian Statistical Methods. Springer.
- Blei, D. M., Kucukelbir, A., & McAuliffe, J. D. (2017). Variational Inference: A Review for Statisticians. Journal of the American Statistical Association.

TEXTE DE DESCRIPTION DU COURS

Welcome to "Foundations of Bayesian Thinking: Mastering Probabilistic Inference!" This course is your gateway to understanding the Bayesian philosophy, unlocking the power of Bayesian probability, and mastering probabilistic inference. Whether you're a data scientist, researcher, or enthusiast, this course equips you with the skills to make informed decisions based on data, while embracing the Bayesian way of thinking.

"Foundations of Bayesian Thinking" commences with a deep dive into the philosophical underpinnings of Bayesianism in "Introduction to Bayesian Philosophy." Explore the historical context, the Bayesian versus Frequentist debate, and the subjective nature of Bayesian probability. In "Basics of Conditional Probability," you'll grasp the fundamental concepts, including the conditional probability formula, independent and dependent events, and their significance.

Bayes' Theorem takes center stage, revealing its derivation, real-world applications, and examples that illustrate its importance. In "Prior, Likelihood, and Posterior," you'll uncover the pivotal role each plays in Bayesian analysis, and how they intertwine in the process of updating beliefs.

"Bayesian Inference and Estimation" elevates your Bayesian skills, focusing on parameter estimation using posterior mean, median, and mode. Discover credible intervals as Bayesian counterparts to confidence intervals. Dive into "Conjugate Priors" and explore their benefits, along with practical examples using common distributions like Beta-Binomial and Normal-Normal. Delve into "Hierarchical and Empirical Bayes," mastering multi-level modeling and shrinking estimates with empirical Bayes.

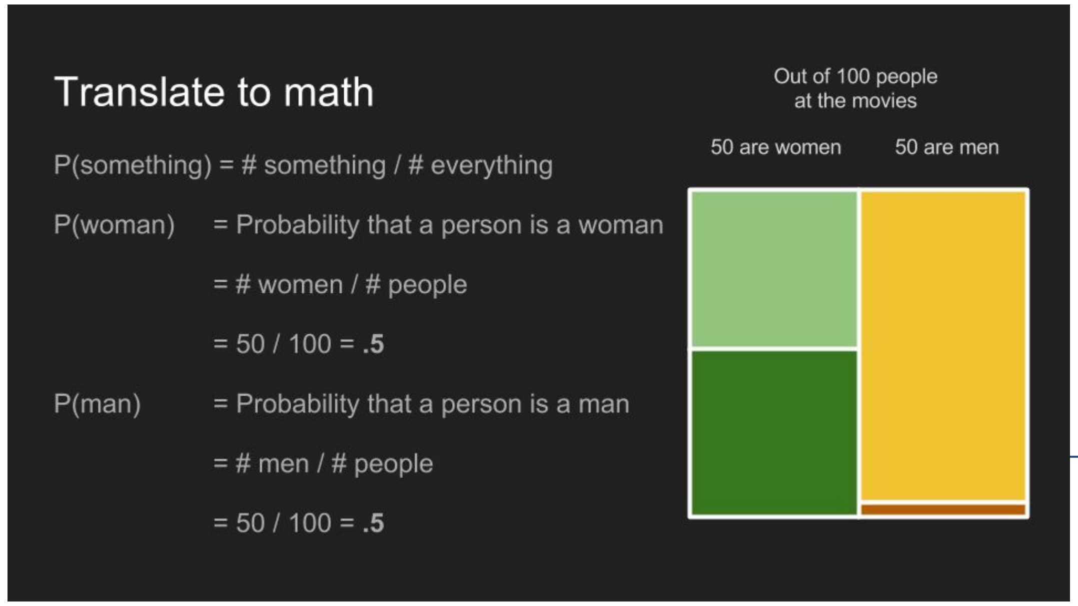
The course proceeds to "Bayesian Model Selection," where you'll explore Bayesian information criteria (BIC) and other metrics, along with Bayesian model averaging.

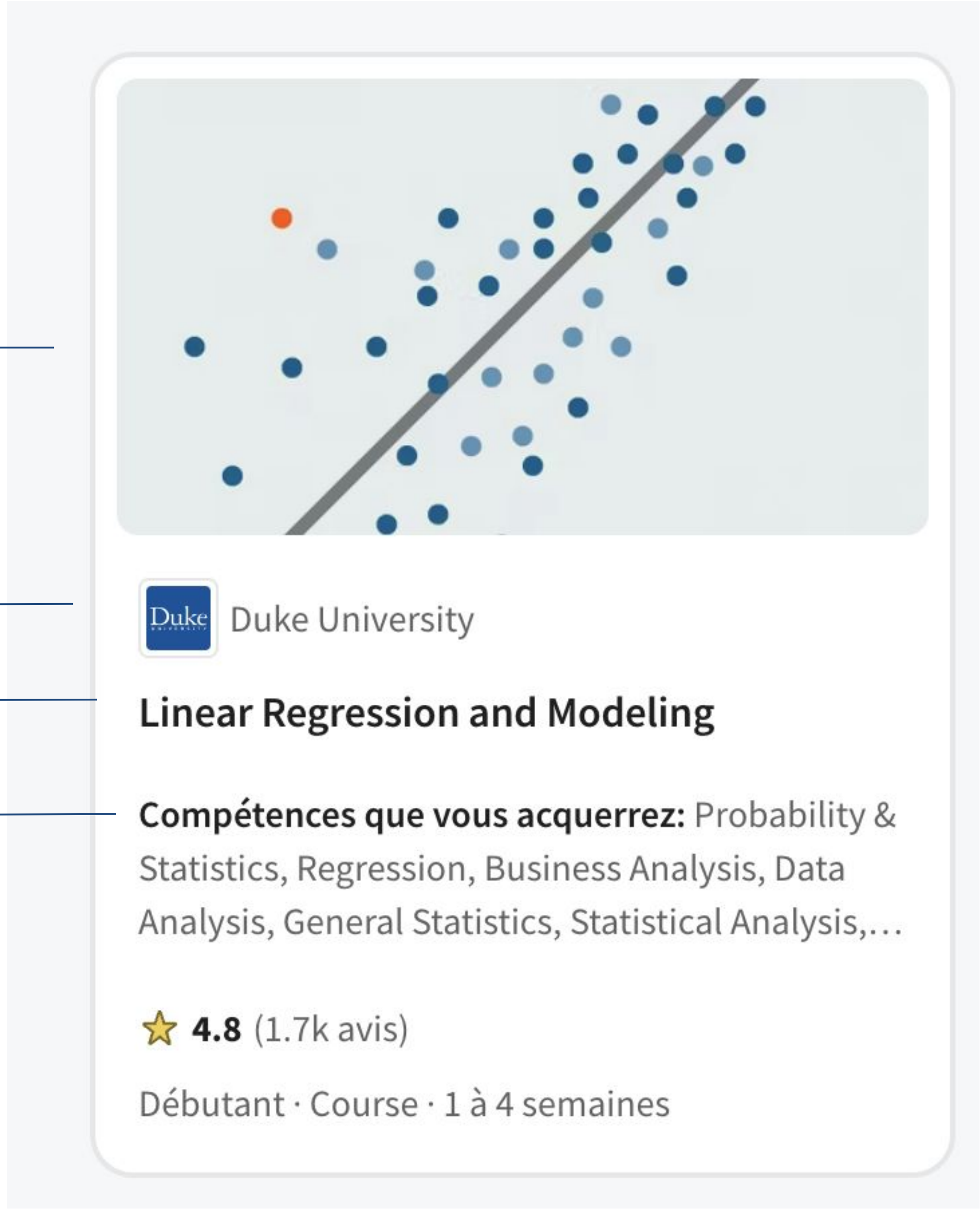
"Computational Methods in Bayesian Analysis" introduces you to the core of Bayesian analysis. Dive into "Markov Chain Monte Carlo (MCMC)," understanding its importance and algorithms like Metropolis-Hastings and Gibbs sampling. Explore advanced MCMC methods in "Hamiltonian Monte Carlo and NUTS," designed for complex models, and understand their benefits and challenges. When likelihood becomes intractable, "Approximate Bayesian Computation (ABC)" comes to the rescue, with principles and applications. Contrast MCMC with "Variational Inference," understanding its use cases and limitations.

"Applications and Challenges" expands your horizons with "Bayesian Networks and Graphical Models." Explore conditional dependencies, d-separation, and inference within Bayesian networks. Discover real-world applications spanning different fields in biology through examples and case studies. Delve into the subjectivity of "Priors and Subjectivity," exploring the dichotomy of objective versus subjective priors and the considerations surrounding them. Finally, tackle the "Challenges and Frontiers" of Bayesian analysis, addressing computational challenges in high-dimensional spaces and exploring the future directions and emerging trends.

By the end of this course, you'll be well-versed in Bayesian thinking, probabilistic inference, and the practical application of Bayesian methods in various domains.

DESIGN DE LA CARD





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Course Name: Simple Linear Regression

#BayesianThinking
#ProbabilisticInference
#BayesianPhilosophy