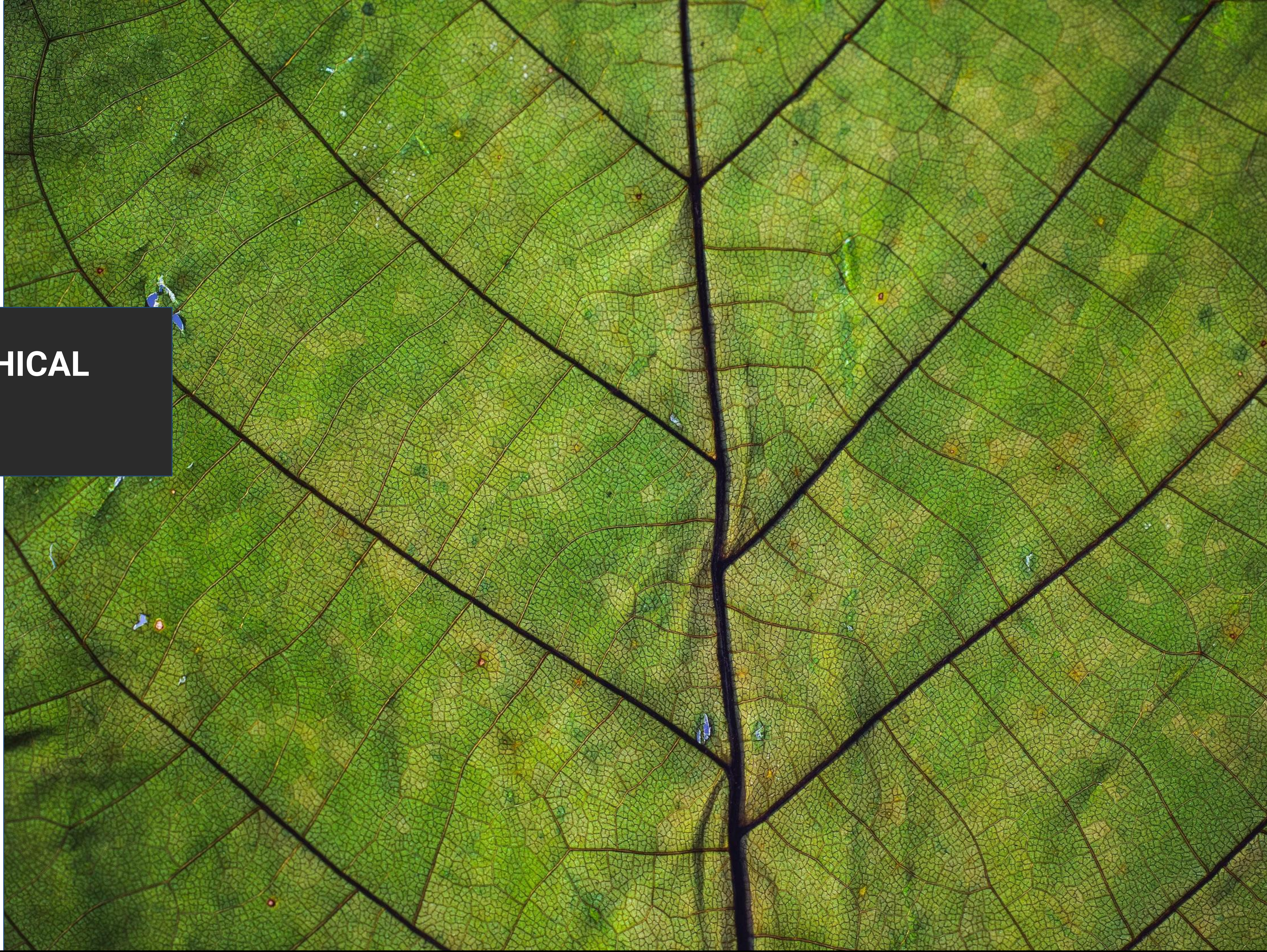
LES FACULTÉS
DE L'UNIVERSITÉ
CATHOLIQUE DE LILLE

Non Linear Models examples

PROBABILISTIC GRAPHICAL MODELS



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KNOWLEDGE TREE

Part 1: Introduction to Graph Theory and Probabilistic Networks

1.1 Basics of Graph Theory

- Definitions: nodes, edges, directed/undirected graphs
- Properties and types of graphs: cycles, trees, and cliques

1.2 Introduction to Probabilistic Graphical Models (PGMs)

- Significance and applications of PGMs
- Types: Bayesian Networks and Markov Networks

1.3 Joint Probability Distributions

- Definition and significance
- Factorization in PGMs

1.4 Independence and Conditional Independence

- D-separation and I-maps
- Conditional independence in Bayesian and Markov Networks

Part 2: Bayesian Networks

2.1 Structure and Semantics

- Directed Acyclic Graphs (DAGs)
- Conditional Probability Distributions (CPDs)

2.2 Inference in Bayesian Networks

- Exact inference: Variable Elimination, Clique Trees
- Approximate inference: Sampling methods

2.3 Learning Bayesian Networks

- Structure learning: Constraint-based, score-based approaches
- Parameter learning

2.4 Real-World Applications

- Medical diagnosis
- Fraud detection

Part 3: Markov Networks

3.1 Structure and Representation

- Factor graphs
- Potential functions

3.2 Inference in Markov Networks

- Max-product and sum-product algorithms
- Loopy belief propagation

3.3 Learning Markov Networks

- Learning the structure
- Learning the parameters

3.4 Challenges and Limitations

- Normalization challenges
- Complexity and scalability issues

Part 4: Advanced Topics and Practical Applications

4.1 Temporal Models

- Hidden Markov Models (HMMs)
- Dynamic Bayesian Networks

4.2 Decision Networks

- Introduction and structure
- Applications in decision-making

4.3 Continuous and Mixed Models

- Gaussian Networks
- Hybrid models with discrete and continuous variables

4.4 Tools and Software

- Introduction to software like BayesiaLab, HUGIN, and pgmpy in Python
- Practical examples and demonstrations

KEYWORDS (NEW)

Path analysis
Propagation de la croyance
Inférence dans les modèles graphiques
Probabilité conditionnelle locale
Probabilité a posteriori
Nœud
Variable latente
K2 Algorithm
Structural equation modelling
Modèle de Markov à champs locaux (MRF)
Propagation de croyance
Probabilité a priori
Parents
Variable observable
Variable aléatoire cachée
Modèles à équations structurelles (LISREL)
Réduction de dimension bayésienne
Probabilité conditionnelle
Modèle de mélange
Postérieur
Inférence exacte
Variable latente gaussienne
Algorithme de croyance à propagation (Belief Propagation)
Réseau bayésien à arêtes latentes
Réseau bayésien
Influence globale
Intrication
Influence directe
Apprentissage de structure
Algorithme de message de croyance (Belief Propagation)
Réseau bayésien dynamique
Validation croisée
Influence indirecte
Enfant
Modèle discriminatif
Modèle de mélange gaussien
Analyse des données manquantes dans les modèles graphiques
Modèle bayésien non paramétrique
Inférence approximative
Modèle génératif
Arête
Modèle de réponse graduée
Autres modèles non linéaires ou bayésiens
Modèle d'énergie conditionnelle (CRF)
Modèle de Markov caché (HMM)
Algorithme EM (Expectation-Maximization)
Modèle de réponse implicite
Analyse de données manquantes dans les réseaux bayésiens
Modèle de Boltzmann restreint (RBM)
Modèles graphiques probabilistes
Estimation du maximum a posteriori (MAP)
Modèle graphique bayésien
Champ aléatoire de Markov
Graphe acyclique dirigé (DAG)
Ensemble de données de test
Algorithme espérance-maximisation
Modèle hiérarchique bayésien
Hypothèse de Markov locale
Ensemble de données d'apprentissage
Algorithme Loopy Belief Propagation

ADD to tree (NEW)

- Path analysis
- Propagation de la croyance
- Inférence dans les modèles graphiques
- Probabilité conditionnelle locale
- Probabilité a posteriori
- Nœud
- Variable latente
- K2 Algorithm
- Structural equation modelling
- Modèle de Markov à champs locaux (MRF)
- Propagation de croyance
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- Ensemble de données de test
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- Modèle hiérarchique bayésien
- Hypothèse de Markov locale
- Ensemble de données d'apprentissage
- Algorithme Loopy Belief Propagation

Part 5: Undirected Graphical Models

5.1 Markov Graphs and their Properties

- Markov Graphs
- Properties of Markov Graphs

5.2 Undirected Graphical Models for Continuous Variables

- Introduction to Continuous Variables
- Estimations of the parameters when the graph structure is known

5.3 Estimation Of The Graph Structure

- Introduction to Graph Structure Estimation
- Methods of Estimation

5.4 Undirected Graphical Models for Discrete Variables

- Introduction to Discrete Variables
- Estimation of the parameters when the graph structure is known

5.5 Exercises on Hidden Nodes and Estimations Of The Graph Structure

- Exercises on Hidden Nodes
- Estimation Of The Graph Structure

5.6 Restricted Boltzmann Machines

- Introduction to Restricted Boltzmann Machines
- Applications and Practical Examples

KEYWORDS

- Graph Theory
- Probabilistic Graphical Models
- Bayesian Networks
- Markov Networks
- Joint Probability Distributions
- Independence
- Conditional Independence
- Directed Acyclic Graphs (DAGs)
- Conditional Probability Distributions (CPDs)
- Inference
- Variable Elimination
- Clique Trees
- Sampling Methods
- Structure Learning
- Parameter Learning
- Hidden Markov Models (HMMs)
- Dynamic Bayesian Networks
- Decision Networks
- Gaussian Networks
- Hybrid Models
- Software Tools
- BayesiaLab
- HUGIN
- pgmpy
- Python
- Practical Examples
- Demonstrations

Use Case with python

Use Case: Medical Diagnosis Using Bayesian Networks

In the context of the course on Graph Theory and Probabilistic Networks, which covers topics related to graph theory basics, probabilistic graphical models (PGMs), Bayesian networks, Markov networks, and their real-world applications, let's explore a use case related to medical diagnosis using Bayesian networks.

Description:
In this use case, we will leverage Bayesian networks, a type of probabilistic graphical model, to assist in medical diagnosis. Bayesian networks are particularly well-suited for modeling complex relationships between medical symptoms and diseases while considering conditional dependencies and uncertainties.

Key Components:
Basics of Graph Theory: Understanding fundamental concepts such as nodes, edges, directed graphs, and undirected graphs. Recognizing properties and types of graphs, including cycles, trees, and cliques.

Introduction to Probabilistic Graphical Models (PGMs): Gaining insights into the significance and applications of PGMs, including Bayesian networks and Markov networks. Understanding their role in modeling probabilistic relationships.

Joint Probability Distributions: Exploring joint probability distributions, their definitions, and importance in PGMs. Emphasizing factorization in PGMs to represent complex distributions efficiently.

Independence and Conditional Independence: Learning about independence and conditional independence concepts in the context of PGMs. Introducing D-separation and I-maps as tools for assessing independence.

Medical Diagnosis Scenario:

Imagine a scenario in which a Bayesian network is employed to aid in the diagnosis of a specific medical condition, such as diabetes. The network incorporates various observable symptoms (e.g., increased thirst, frequent urination) and diagnostic test results (e.g., blood glucose levels) as nodes in the network. The goal is to estimate the probability of a patient having diabetes based on the available information.

Python Code Example (Simplified Bayesian Network for Medical Diagnosis):

```python
import numpy as np
import pgmpy.models
import pgmpy.factors.discrete
from pgmpy.inference import VariableElimination

# Define the Bayesian Network structure (DAG)
model = pgmpy.models.BayesianNetwork([('Symptom1', 'Diabetes'), ('Symptom2', 
'Diabetes')])

# Define conditional probability distributions (CPDs)
cpd_symptom1 = pgmpy.factors.discrete.TabularCPD(
    variable='Symptom1',
    variable_card=2,  # 2 states: Present, Absent
    values=[[0.8], [0.2]]  # P(Symptom1)
)

cpd_symptom2 = pgmpy.factors.discrete.TabularCPD(
    variable='Symptom2',
    variable_card=2,  # 2 states: Present, Absent
    values=[[0.7], [0.3]]  # P(Symptom2)
)

cpd_diabetes = pgmpy.factors.discrete.TabularCPD(
    variable='Diabetes',
    variable_card=2,  # 2 states: Positive, Negative
    values=[[0.9, 0.6, 0.7, 0.1], [0.1, 0.4, 0.3, 0.9]],  # P(Diabetes | 
    Symptom1, Symptom2)
    evidence=['Symptom1', 'Symptom2'],
    evidence_card=[2, 2]
)

# Add CPDs to the model
model.add_cpds(cpd_symptom1, cpd_symptom2, cpd_diabetes)

# Check the model for consistency
model.check_model()

# Perform inference using Variable Elimination
inference = VariableElimination(model)
result = inference.query(variables=['Diabetes'], evidence={'Symptom1': 0, 
'Symptom2': 1})

print(result)
```

In this code, we construct a Bayesian network to model the relationship between symptoms (Symptom1 and Symptom2) and the presence of diabetes (Diabetes). We define conditional probability distributions (CPDs) based on hypothetical probabilities. The pgmpy library is used for Bayesian network modeling and inference.

This use case demonstrates how Bayesian networks can help in medical diagnosis by quantifying the probability of a condition given observed symptoms and test results.

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TEXTE DE DESCRIPTION DU COURS

This course provides a comprehensive overview of Graph Theory and Probabilistic Networks. It begins with an introduction to the fundamentals of Graph Theory, covering concepts such as nodes, edges, and different graph types, including directed and undirected graphs, cycles, trees, and cliques. The course then delves into Probabilistic Graphical Models (PGMs), exploring their significance and applications, along with a focus on Bayesian Networks and Markov Networks.

In the first part of the course, you'll learn about Joint Probability Distributions and their factorization within PGMs, as well as concepts of independence and conditional independence, including D-separation and I-maps.

Moving on to Bayesian Networks, the course discusses their structure, semantics, and the role of Directed Acyclic Graphs (DAGs), along with Conditional Probability Distributions (CPDs). Inference in Bayesian Networks is explored, covering both exact methods like Variable Elimination and Clique Trees, as well as approximate techniques like Sampling methods. Additionally, you'll delve into learning Bayesian Networks, including structure learning and parameter learning, with practical applications in fields such as medical diagnosis and fraud detection.

The course then transitions to Markov Networks, discussing their structure and representation through factor graphs and potential functions. Inference in Markov Networks is explored through algorithms like max-product and sum-product, as well as Loopy belief propagation. Learning Markov Networks, both in terms of structure and parameters, is also covered, along with an examination of challenges and limitations, including normalization issues and scalability concerns.

The final part of the course delves into advanced topics and practical applications, including Temporal Models like Hidden Markov Models (HMMs) and Dynamic Bayesian Networks. Decision Networks are introduced, emphasizing their structure and applications in decision-making. Continuous and Mixed Models, such as Gaussian Networks and hybrid models combining discrete and continuous variables, are explored. The course concludes with an introduction to relevant software tools like BayesiaLab, HUGIN, and pgmpy in Python, accompanied by practical examples and demonstrations to reinforce your understanding.

DESIGN DE LA CARD

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Course Name: Simple Linear Regression

#Graph Theory
#Probabilistic Networks
#Bayesian Inference