**10-708 – Probabilistic Graphical Models**

A pedagogical tool to track the key aspects of the lecture that the instructor emphasises, and as a checklist of things you have judged are important.

Some content is given little weight in the lectures for time-keeping purposes. They are listed in italics, and you must make a judgement on whether it is necessary to allocate time to understanding them.

**Key areas to understand**

**Week 1**

Lecture 1 – Introduction

* Understand that probabilistic graphical models as a language for representing complex probability distributions, reasoning under uncertainty and noise.
* Understand the intractability of working with full joint probability tables.
* Understand the benefits of probabilistic graphical models in this context.
* Understand the formal definition of a probabilistic graphical model.
* Understand that graph structure, topology, and conditional independence can be used to encode domain knowledge and yield representational cost-savings.

Lecture 2 – Directed Graphical Models

* Understand that Bayesian Networks/Directed Graphical Models have directed edges - causality relationships.
* Understand that Markov Random Fields/Undirected Graphical Models have undirected edges- correlation relationships.
* Understand the notational conventions of the course.
* Understand the HMM dishonest casino model in context of the knowledge engineering process.
* Understand the definition and properties of a Bayesian Network, the factorisation theorem, and the role of conditional independence.
* Understand the local structures and independencies.
* Understand the I-maps.
* Understand “explaining away”
* Understand the “d-separation criterion” on moralised ancestral graphs.
* Understand equivalence theorem.
* Understand “soundness” and “completeness” of d-separation with respect to a Bayesian Network factorisation law.
* Understanding of the concepts mathematically, but also be able to rehearse the semantics.
* *Understand the identifiability of local and global independence of Bayesian Networks via d-separation and the Bayes ball.*