

# Lecture 1a. StatML Welcome

COMP90051 Statistical Machine Learning

Sem2 2020

Lecturer: Ben Rubinstein



THE UNIVERSITY OF  
MELBOURNE

# This lecture

- **About COMP90051**
- Review: Probability theory
- Review: Linear algebra
- Review: Sequences and limits

# Subject objectives

- Develop an appreciation for the role of statistical ML, advanced foundations and applications
- Gain an understanding of a representative selection of ML techniques – *how ML works*
- Be able to design, implement and evaluate ML systems
- Become a discerning ML consumer

# Subject content



**30%+ new  
content**

- The subject will cover topics from  
Foundations of statistical learning, linear models, non-linear bases, regularised linear regression, generalisation theory, kernel methods, deep neural nets, multi-armed bandits, Bayesian learning, probabilistic models
- Theory in lectures; hands-on experience with range of toolkits in workshop pracs and projects
- vs COMP90049: **much depth**, **much rigor**, **so wow**

# Subject staff / Contact hours

Contacting staff	<i>Discussion board first; then combined staff email</i> <b><a href="mailto:comp90051-2020s2-staff@lists.unimelb.edu.au">comp90051-2020s2-staff@lists.unimelb.edu.au</a></b>
Lecturer & Coordinator	Ben Rubinstein Associate Prof, Computing & Information Systems Associate Dean (Research), Melbourne School of Engineering <i>Statistical Machine Learning, ML + Privacy/Security/Databases</i>
Lecturer	Qihong Ke Lecturer, Computing & Information Systems <i>Computer Vision, ML, Deep Learning</i>
Tutors:	Neil Marchant (Head Tutor) Justin Tan, Jun Wang, Rui Zhang. <i>See Canvas for latest list and contact details.</i>
Zoom Contact:	<i>Weekly, please attend: 2nd Lecture (live discussion), 1 Workshop</i>
Pre-recorded Lectures:	<i>Posted to Canvas for you to view safely at home.</i> Strongly recommend that you keep up, weekly. (viz. quizzes)

# About me (Ben)

- PhD 2010 – Berkeley, USA
- 4 years in **industry research**
  - \* Silicon Valley: Google Research, Yahoo! Research, Intel Labs, Microsoft Research
  - \* Australia: IBM Research
  - \* Patented & Published, Developed & Tested, Recruited
- **Impact:** Xbox, Bing (MS), Firefox (Mozilla), Kaggle, ABS, Medicare and Myki data privacy
- **Interests:** machine learning theory; adversarial ML; differential privacy; statistical record linkage

# *Advanced* ML: Expected Background

- Why a challenge: Diverse math + CS + coding
- ML: COMP90049 either 2020s1 “new” or earlier (we’ll review gaps throughout semester)
- Alg & complexity: big-oh, termination; basic data structures & algorithms; solid coding ideally experience in Python

...and more...

# Advanced ML: Expected Background

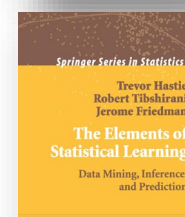
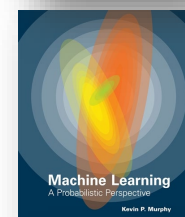
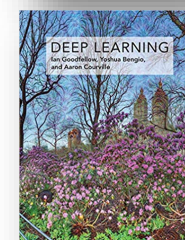
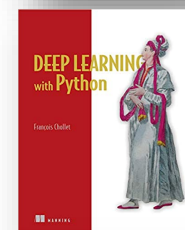
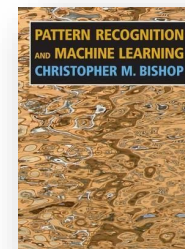
...and more...

- Maths: Review next videos, but ideally seen most before  
*“Matrix  $\mathbf{A}$  is symmetric & positive definite, hence its eigenvalues...”*
- **Probability theory**: probability calculus; discrete/continuous distributions; multivariate; exponential families; Bayes rule
- **Sequences**: sequences, limits, supremum
- **Linear algebra**: vector inner products & norms; orthonormal bases; matrix operations, inverses, eigenvectors/values
- **Calculus & optimisation**: partial derivatives; gradient descent; convexity; Lagrange multipliers



# Textbooks

- We **don't have only one reference**. We prefer to pick good bits from several. We may also supplement with other readings as we go.
- All are available free online or through the library digitally. See the **Canvas lecture outline** for links. Therefore, **no need to buy**.
- Primarily we refer to (good all rounder): Bishop (2007) *Pattern Recognition and Machine Learning*
- Practical Deep Nets: Chollet (2017) *Deep learning with Python*
- More deep learning detail: Goodfellow, Bengio, Courville (2016) *Deep learning*
- For more on PGMs/Bayesian inference: Murphy (2012) *Machine Learning: A Probabilistic Perspective*
- For reference on frequentist ideas, SVMs, lasso, etc.: Hastie, Tibshirani, Friedman (2001) *The Elements of Statistical Learning: Data Mining, Inference and Prediction*



# Assessment

- Assessment components
  - \* Two projects – one group (w4-7), one individual (w9-11)
    - Each (30%)
    - Each has ~3 weeks to complete
  - \* Final Exam (40%)
- 50% hurdles applied to both **exam** and **combined project**
- Ungraded semi-weekly **quizzes**.  
Completion expected that week, please

# Summary

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Homework week #1: Watch all week 1 recordings.  
Jupyter notebooks setup and launch (at home)