#### Lecture 24. Revision

(the content of this deck is non-examinable)

COMP90051 Statistical Machine Learning

Semester 2, 2016
Lecturers: Trevor Cohn, WHard,
brainRover, Andrey Kan



#### This lecture

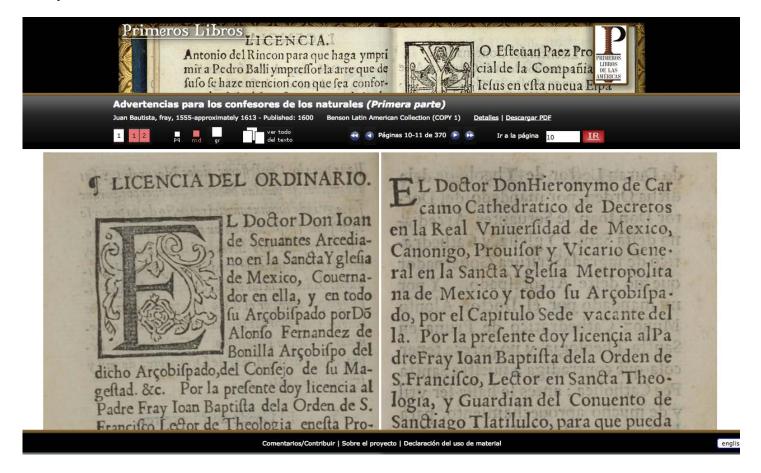
- Project notes and team presentations
- Exam tips
- A deeper insight
- Reflections on the subject
- Q&A session / office hour

# Project Notes and Team Presentations

Well done every team!

#### Project Data: Primeros Libros

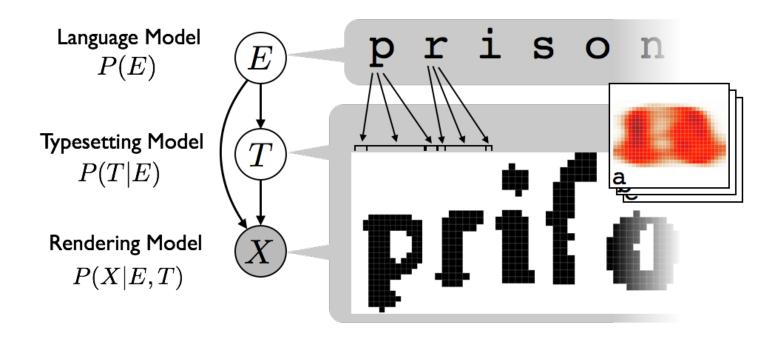
Texts printed in Mexico in the 1500s



#### Books used

Gante	(1553)	motlacatilia: ynica sacramento Baptis
Sahagún	(1583)	Yoan oquilhui in Emperador, inglaça
Rincón	(1595)	ction.v.g.tetlaçotlaliztli.amatio, vel,
Bautista	(1600)	Rimo, bæc supra dictus doctor Medina. Mas

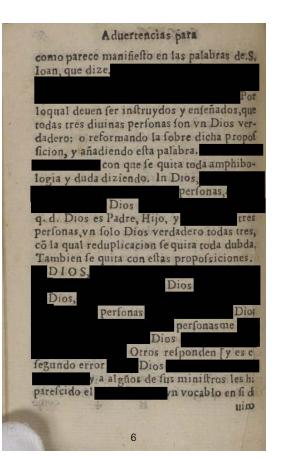
#### Overview: Ocular OCR system (Berg-Kirkpatrick et al, 2013)



Observe ONLY the image; infer the font and rendering components using EM algorithm.

(Also know likely character sequences in the language[s] from modern texts.)

#### Multilingual texts: Spanish, Latin & Nahuatl



#### Aduertencias para

como parece manifiesto en las palabras de.S. Ioan, que dize. Tres funt qui testimonia dat in celo Pater, Verbum, & Spiritusfanctus : & hi tres vnum funt, I. loann, vltimo Por loqual deuen fer instruydos y enfeñados, que todas tres diuinas personas son vn Dios verdadero: o reformando la fobre dicha propof sicion, y anadiendo esta palabra. In huel ime ixtintzitzin, con que se quita toda amphibologia y duda diziendo. In Dios ca Tettatzin Tepiltzin, Spiritu fancto, ei personas, çan ce huelnelli teutl Dios in huel imeixtintzitzin, q. d. Dios es Padre, Hijo, y Spu sancto tres personas vn solo Dios verdadero todas tres, co la qual reduplicación se quira coda dubda, Tambien se quita con estas propossiciones. In DIOS,ca Tettatzin, Tepiltzin, Spiritulan &o. can huel icelezin reutl Dios tlahtohuani, In Dios, ca Tettarzin, Tepilizin, Spiritufan. do, imeixtin personas can huel iceltzin Dio tlahtohnani. Ca inimeixtin personasme cacan huel iceltzin teutl Dios tlahtohuani in. huel imeixtin. T Otros responden [y es c fegundo error ] ça ce Dios tlahtohuani, imme teilittotica, y a alossos de sus ministros les hi parescido el meteintrorica, vn vocablo en si di



# Transcriptions: their evaluation vs. our training

#### Aduertencias para

como parece manifiesto en las palabras de.S. Ioan, que dize. Tres funt qui testimonia dat in colo Pater, Verbum, & Spiritusfanctus: & hi tres vnum funt, t. loann, vltimo Por loqual deuen fer instruydos y enfeñados, que todas tres diuinas personas son vn Dios verdadero: o reformando la sobre dicha propos ficion, y añadiendo esta palabra. In huel ime ixtintzitzin, con que se quita toda amphibologia y duda diziendo. In Dios ca Tettatzin Tepiltzin Spiritu fancto, ei personas, gan ce huelnelli teutl Dios in huel imeixtintzitzin, q. d. Dios es Padre, Hijo, y Spa sancto rres personas vn solo Dios verdadero todas tres, co la qual reduplicación se quita toda dubda, Tambien se quita con estas propossiciones. In DIOS, ca Tettatzin, Tepiltzin, Spiritulan &o.can huel icelezin reucl Dios tlahtohuani, In Dios, ca Tettarzin, Tepilezin, Spiritufan. &o, imeixtin perfonas can huel iceltzin Dios tlahtohuani. Ca inimeixtin personasme caçan huel iceltzin teurl Dios tlahtohuani inhuel imeixtin. T Otros responden [y es c fegundo error | ça ce Dios tlahtohuani, imme teihttotica, y a algños de sus ministros les hi parescido el mereintrorica vn vocablo en si d

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#### Processing pipeline

- Normalise colour
- Extract lines
- 3. Apply tesseract OCR
- 4. Edit distance alignment to manual transcription
- 5. Extract example for (char, region from image)

#### MISTICA

ya dicho de los peccados ré por regla que toda confideración que vieres que mas re mueue a alcácar aquel dolor aquella fea tu via purgariua mictra en ella le hallares agora fea del infierno, agora fea de la muerte o otra qualquiera. Mas por quanto estavia que aqui se pone es precursora de las dos que se figuen en las quales apro ue cha mucho acostubrar el anima a se lepantar hazia arriba ponese aqui vn modo el qual parece mas coforme alo q fe figue no obstâte que la regla ya dicha se quede en fuvigor el qual es el que fe figue. Primeramente recogido en algun lugar le creto yespecialmente de noche trayga ala memoria diez o doze de los mas graues de sus peccados, y los de mas passe assi en general y breuemente en especial si fon carnales, o otros que puedan traer algun deleyre, y no fe detenga en ellos por que lo que bufca para dolor, el demonio no le trayga a culpa Y leuantando fu cara alcie lo como fiestouiesse delante elacatamiéto de Dios hablando con el cuente los con

#### MISTICA

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ya dicho de los peccados t\~e por regla que

#### Team presentations

- WHard
  - \* Ranked 3<sup>rd</sup> with the score of 0.83986
- brainRover
  - Ranked 2<sup>nd</sup> with the score of 0.84715

# OUR SOLUTION

Team: Whard

Team members: Han Yu, Yiheng Wang, Xing Han



#### **PREPROCESSING**

padding image to 33\*33

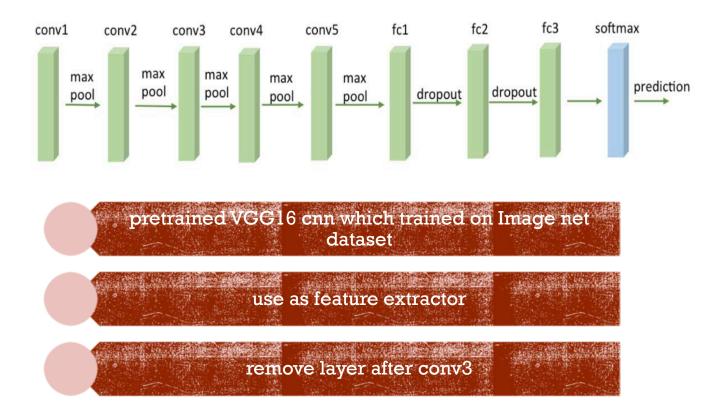
move character to the center of image

resize it to 32\*32

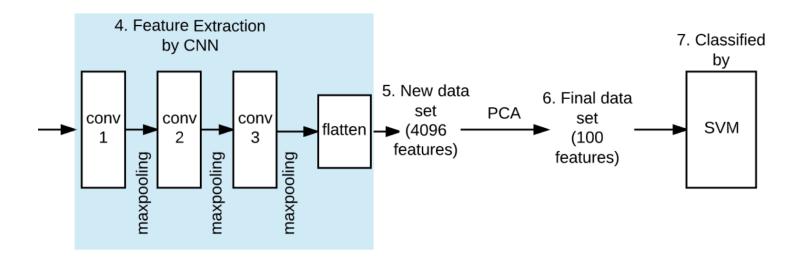
transform it to RGB



#### VGG16



## SVM + VGG16



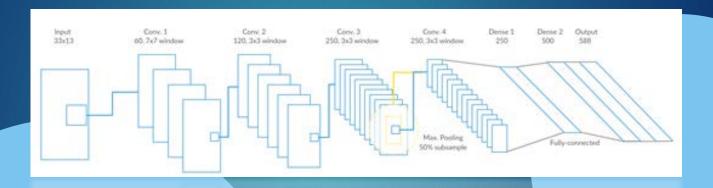
#### COMP90051: Statistical Machine Learning

**Project:** OCR for Historical Documents Notes on Team BrainRover's Approach

#### Preprocessing

- 1. Quality control and culling obvious errors
  - Particularly important for rare classes
- 2. Oversampling rare classes
- 3. Affine transformations using ImageDataGenerator in Keras
  - Create believable transformations to emulate unseen data
  - Random shear, zoom, rotation, width/height shift
  - Reduce overfitting by enlarging the dataset

#### Topology



- 1. Input
- 2. C1: 60, 7x7
- 3. C2: 120, 3x3
- 4. C3: 250, 3x3
  - Max. pooling
- 5. C4: 250, 3x3
- 6. D1: 250
- 7. D2: 500
- 8. Output (softmax): 588 (98x6)

- Rectified linear units (ReLUs)
- Dropout imposed on D1 and D2

#### Training

1. Loss function: Categorical cross-entropy

2. Optimisation: Adadelta

3. Samples/epoch: ~50,000, in batches of 800

4. Epochs: 60

5. GPU: NVIDIA GTX1070

## **Exam Tips**

Don't panic ©

#### Exam tips

- Don't panic
- Attempt all questions
  - Do your best guess whenever you don't know the answer
- Finish easy questions first
- Quizzes and practice exam questions are representative of what you might get at the exam
- Make sure you understand solutions for each quiz and practice exam

#### What's non-examinable?

- Green slides
- All of this deck
- Deck 7: Slides on Gaussian blur and Sobel kernel
- Deck 8: Slides on CNNs & RNNs (beyond motivation)
- Deck 16: Slides on LDA, HMMs, vision MRFs (beyond motivation)
- Something that was in workshops but not in lectures
- Note: material covered in the reading is fair-game

## A Deeper Insight

A selection of additional topics with the aim to provide a deeper insight into main lectures content

#### Kernelised perceptron (1/3)

When classified correctly, weights are unchanged

When misclassified: 
$$\mathbf{w}^{(k+1)} = -\eta(\pm \mathbf{x})$$
  
( $\eta > 0$  is called *learning rate*)

$$\begin{array}{ll} \underline{\text{If } y = 1, \, \text{but } s < 0} & \underline{\text{If } y = -1, \, \text{but } s \geq 0} \\ w_i \leftarrow w_i + \eta x_i & w_i \leftarrow w_i - \eta x_i \\ w_0 \leftarrow w_0 + \eta & w_0 \leftarrow w_0 - \eta \end{array}$$

Suppose weights are initially set to 0

First update:  $\mathbf{w} = \eta y_{i_1} \mathbf{x}_{i_1}$ Second update:  $\mathbf{w} = \eta y_{i_1} \mathbf{x}_{i_1} + \eta y_{i_2} \mathbf{x}_{i_2}$ Third update  $\mathbf{w} = \eta y_{i_1} \mathbf{x}_{i_1} + \eta y_{i_2} \mathbf{x}_{i_2} + \eta y_{i_3} \mathbf{x}_{i_3}$  etc.

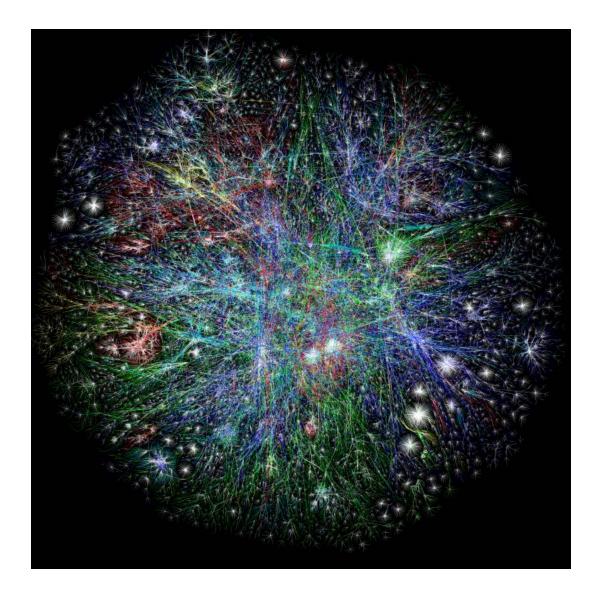
#### Kernelised perceptron (2/3)

- Weights always take the form  $\mathbf{w} = \sum_{i=1}^{n} \alpha_i y_i \mathbf{x}_i$ , where  $\boldsymbol{\alpha}$  some coefficients
- Perceptron weights are always a linear combination of data!
- Recall that prediction for a new point x is based on sign of  $w_0 + w'x$
- Substituting  $\boldsymbol{w}$  we get  $w_0 + \sum_{i=1}^n \alpha_i y_i \boldsymbol{x}_i' \boldsymbol{x}$
- The dot product  $x_i'x$  can be replaced with a kernel

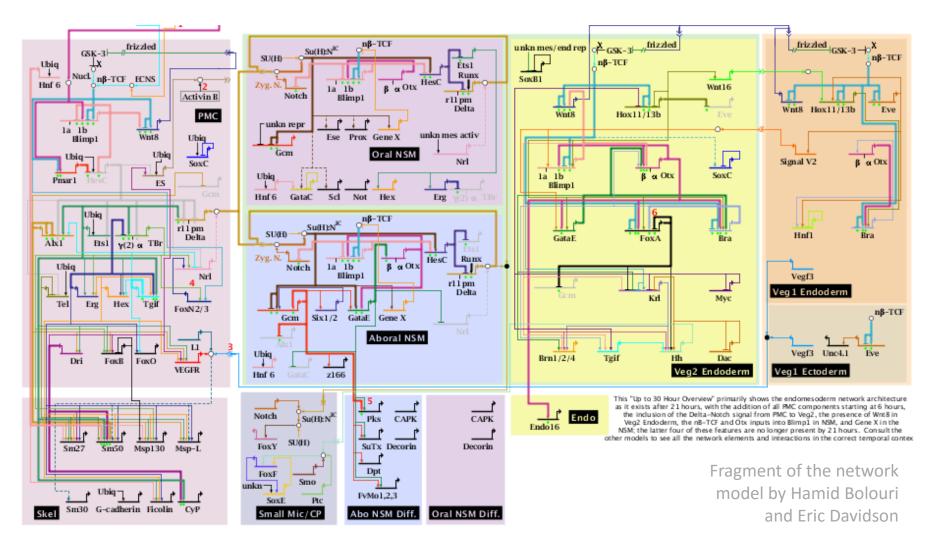
#### Kernelised perceptron (3/3)

- 1. Initialisation: set  $\alpha = 0$
- 2. For each training example  $\{x_j, y_j\}$ 
  - a) Make prediction based on  $w_0 + \sum_{i=1}^n \alpha_i y_i x_i' x_j$
  - b) If the example is misclassified, update  $\alpha_j \leftarrow \alpha_j + 1$
- 3. Repeat Step 2 predefined number of times (number of epochs)

#### Networks in real life: the Internet



#### Networks in real life: gene regulatory network



#### Networks in real life: transport map

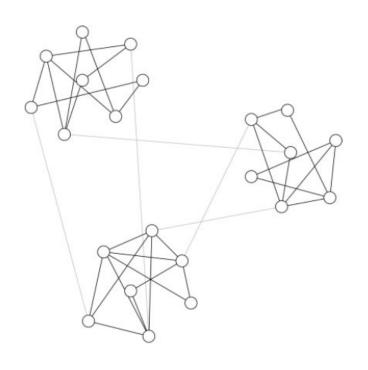


#### Network analysis (1/4)

- Analysis of large scale real world networks has recently attracted considerable attention from research and engineering communities
- Networks/graphs is a list of pairwise relations (edges) between a set of objects (vertices)
- Example problems / types of analysis
  - Link prediction
  - Identifying frequent subgraphs
  - \* Identifying influential vertices
  - Community finding

#### Network analysis (2/4)

- Community is a group of vertices that interact more frequently within its own group than to those outside the group
  - \* Families
  - \* Friend circles
  - Websites (communities of webpages)
  - Groups of proteins that maintain a specific function in a cell
- This is essentially a definition of a cluster in unsupervised learning

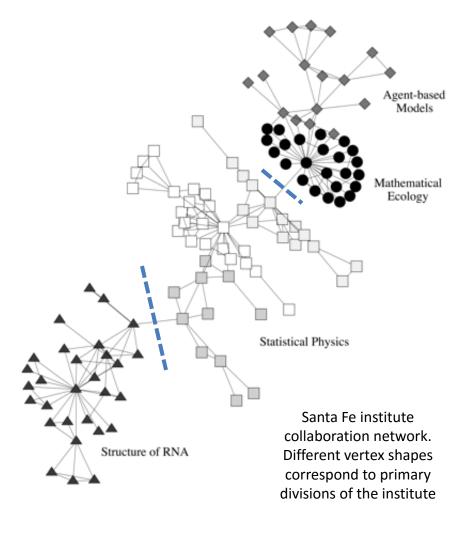


#### Network analysis (3/4)

- Why community detection?
  - \* Understanding the system behind the network (e.g., structure of society)
  - Identifying roles of vertices (e.g., hubs, mediators)
  - Summary graphs (vertices communities, edges connections between communities)
  - \* Facilitate distributed computing (e.g., place data from the same community to the same server or core)
- There are many community detection algorithms, let's have a look at only one of the ideas

#### Network analysis (4/4)

- Communities are connected by a few connections, which tends to form bridges
- Cut the bridges to obtain communities
- One of the algorithms is called normalised cuts which is equivalent to spectral clustering



#### Autoencoder: dimensionality reduction (1/4)

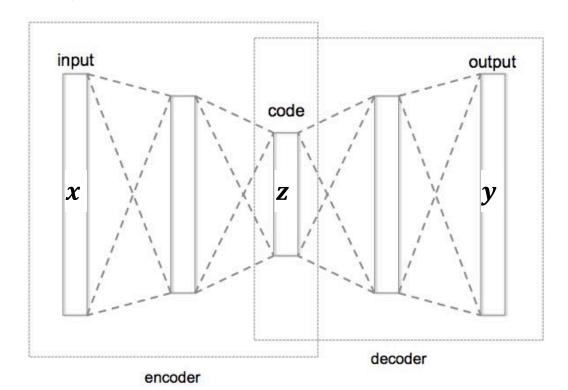
- Supervised learning:
  - \* Univariate regression: predict y from x
  - \* Multivariate regression: predict y from x
- Unsupervised learning: explore  $x_1, ..., x_n$
- For each  $x_i$  set  $y_i \equiv x_i$
- Train a feed forward ANN to predict  $y_i$  from  $x_i$
- Pointless?

#### Autoencoder: dimensionality reduction (2/4)

• For each  $x_i$  set  $y_i \equiv x_i$  and train a feed forward ANN to predict  $y_i$  from  $x_i$ 

• Set the hidden layer  $z_i$  in the middle "thinner" than the

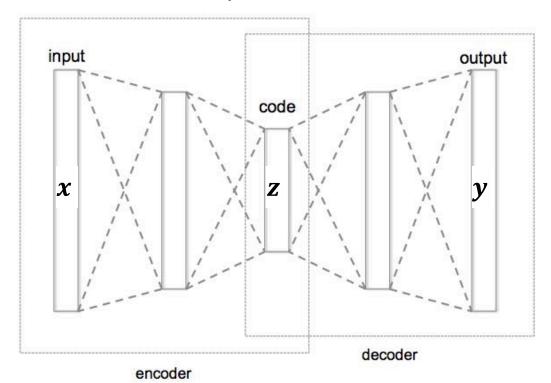
input



adapted from: Chervinskii at Wikimedia Commons (CC4)

#### Autoencoder: dimensionality reduction (3/4)

- Suppose you managed to train a network that gives a good restoration of the original signal  $y \approx x$
- This means that the data structure can be effectively described by a lower dimensional representation z



adapted from: Chervinskii at Wikimedia Commons (CC4)

#### Autoencoder: dimensionality reduction (4/4)

- In general, autoencoders learn a non-linear transformation
- If you use linear activation functions and only one hidden layer, then the setup becomes almost that of PCA
- The difference is that ANN might find a different solution, it doesn't use eigenvalues

# Reflections on the Subject

## Frequentist supervised learning

- Essentially a task of function approximation
- A function can be defined
  - Theoretically, by listing the mapping
  - Algorithmically
  - \* Analytically
- Every equation is an algorithm, but not every algorithm is an equation

## Frequentist supervised learning

- Simple and more interpretable methods (e.g., linear regression) vs more complicated "black box" models (e.g., random forest)
- Apparent dichotomy: prediction quality vs interpretability
- However, some complex models are interpretable
  - Convolutional Neural Networks
  - \* In any "black box" model, one can study effects of removing features to get insights what is a useful feature

### What is Machine Learning?

- Machine learning
  - \* "a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty (such as planning how to collect more data!)" (Murphy)
- Data mining
- Pattern recognition
- Statistics
- Data science
- Artificial intelligence



We'll first stay here, then move to the office hour room

## Thank you and good luck!