FROM MODEL TO PRODUCTION

CONSTRAINTS

CAPABILITES

underestimate over estimate -→ poor results overestimate underestimate _ → didn't attempt a soluable problem - fail to consider and react to Important issues might not try things that may be beneficial

HOW TO START?

- 1 select a project D consider data availability !
- 2) start quickly o don't wait for perfection in data, pipeline, etc.
- 3 create a full project pipeline Diterate from end to end D if mobile app is the goal of the project D have it after each iteration
 - 🖈 see where the tricky bits are
 - A gain better understanding of data needs; availability us needs
 - * will have a working prototype to show
- ④ iterate in small increments D document findings

STATE OF DEEP LEARNING (2020)

- COMPUTER VISION -

- ✓ recognize items in an image at least as well as people (even radiologists) > OBJECT RECOGNITION
- ✓ Location of objects in an image; highlight the location and name each found object
 - =) OBJECT DETECTION
 - Image labeling can be slow and expensive ✓ synthetically generate variations of input images (e.g. rotating, ch. trightness, contrast, ...) = DATA AUGHENTATION
- √ categorizing every pixel ⇒ SEGHENTATION
- * recognizing images structurally or instyle diff. than the training images. DOUT- OF - DOMAIN DATA Dlearn how to manage for models in production
- ✓ convert non-image problem into a cv problem: D classification of sound

NATURAL LANGUAGE PROC. (TEXT).

- ✓ classifing short / long documents Despam ylv, sentiment, author, website,...
- y generating context appropriate text ▶ replies to social media, imitating author's style
- x generating correct responses!
- y used to spread disinformation ocreate unrest
- > encourage conflict Text generation models always ahead of models for recognizing automatically gener. text ▶ viscious circle (use M2 to improve MI)
- ✓ translate text | Summarize long documents | find all mentions of a concept of interest ...
- ▶ protein chains as NLP problem \$

·TEXT 子 IMAGES -

> train on images with captions => generate captions on new images ? always check whether the captions are correct

DL should not be used as an entirely automated Process !

human interaction is essential

can make humans much more productive & more accurate

example DL system identifies potential stroke victims from CT scans D send high-prority alert for the scans to be checked out by a human

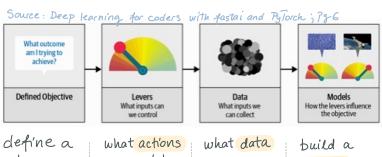
TABULAR DATA

- recently making great strides in DL
- > 1 variety of columns to include
 - -> text I high cardinality categorical columns
- > take long time to train vs. RF/GBM =) RAPIDS is changing this with GPU acceleration for the whole model Pipeline

RECOMMENDATION SYSTEMS-

- ▶ special type of tabular data . HCCV ▶ high cardinality categiver users & products
- ✓ DL models are good at handling HCCV
- y tells us which products a user might like us. what recommendations would be kelpful for a user.

THE APPR DACH => consider how your model will be used in practice DRIVE TRAIN



need a systematic design approah to build sophisticated data science products

clear objective pašk what poblem are you trying to solve

you need to you have; model take to meet structure your defined objective

Produce actionable results!

Example: Google search engine

Example: Recommendation System

ask about what the user wants > the most relevant results > objective is to show them

rank the what new data to consider search resuts > which pages linked to which other pages

drive additional sales by reommencling items that would not be purchased otherwise

collect new ranking data of the D conduct recommenda-Hons many randomized expeniments (wide range of customers +

tions

D2 models for purchase probabilities conditional on seeing or not seeing a 1000mmendation recommenda-

difference of two models is the utility func. for a given recomm. for a customer.

GATHERING DATA

D find data online D Bing Image Search | Duck Duck Go D make sure your data is not Diased

consider what type of data your application will encounter

"Actionable Auditing: Investigating the Impact of Publicly Naming Biased Performance Results Of Commercial Al Products"; Deb Raji

all data types should be included in the input data for the model

PROCESS

o download images

o verify images or there are always failed images ? I unlink them

o structure data in a format suitable for training Do Data Loaders

DATA AUGMENTATION: roundow variation of input data images appear different but do not change meaning of data rotation II flipping II perspective warping II brightness changes Il contrast changes batch_tfms

applied on images
of the same size

o train the model

O CONFUSION MATRIX >> Check in which classes the model is making mistakes the most

Predicted >>> calculated using the validation set

O TN FP
O TN TP

TN: true negative } correct padiations
TP: true positive }

FP: false positive: falsly predicting positive event FN: false negative: falsy predicting negative event