

CRASH!

Practical Applications of Deep Learning in the Insurance Claims Industry

NIGEL CANNINGS
CTO



WHO ARE INTELLIGENT VOICE?



Established in 2010

25 Employees Worldwide

Offices in London, New York and San Francisco



INTELLIGENT VOICE

Intelligent Voice indexes key words and phrases from your telephone calls



SPEECH-TO-TEXT

This allows you to search for telephone calls as if they were text.



ANALYZE

Add-on modules give you the power to analyze calls and track anomalous behavior.



200X FASTER

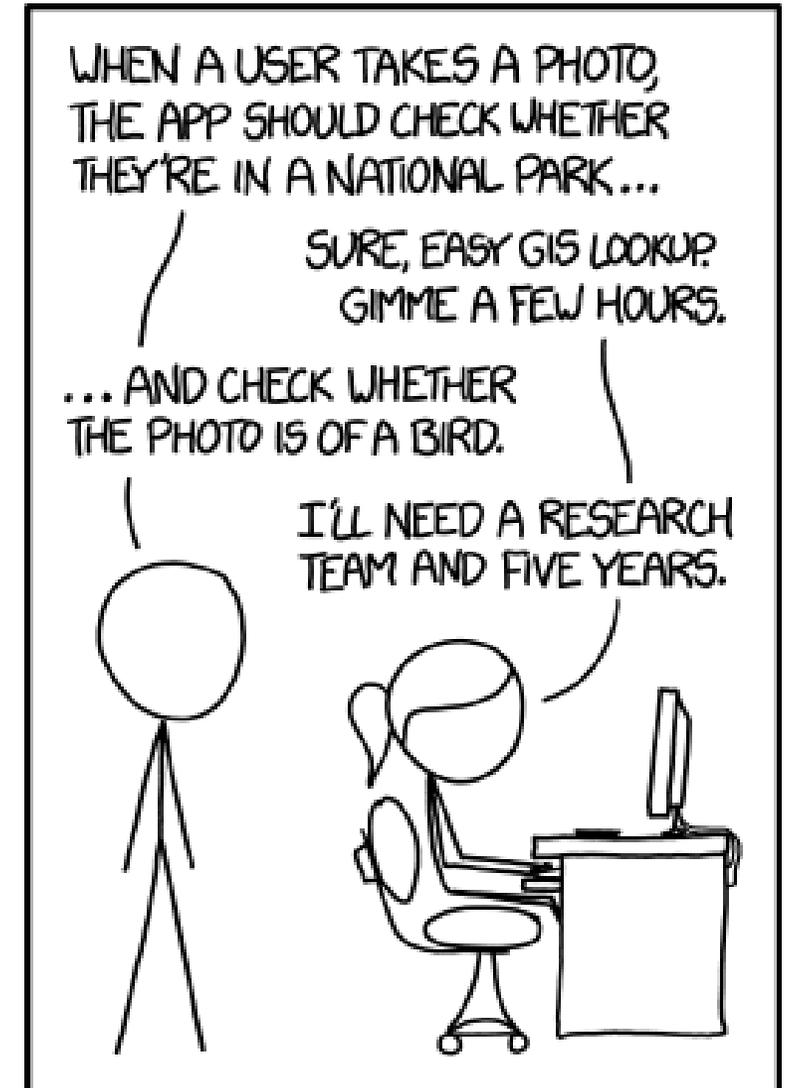
Nvidia® GPU technology
Processes calls at up to 200X
Faster than real time per card.

WE ARE ALL
SCREWED



CAR INSURANCE DAMAGE ASSESMENT

- Use Case
- Sales Perspective – All we want to do is automatically assess damage to cars



IN CS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALLY IMPOSSIBLE.

IMAGE QUALITY

- Reflections
- Shadows
- Blurring
- Colour/GrayScale
- Orientation
- Resolution



CONVOLUTIONAL NEURAL NETWORK

- Bio-inspired from receptive fields
- State of the art is progressing fast
- GPU acceleration

(1980) ● Fukushima's NeoCognitron

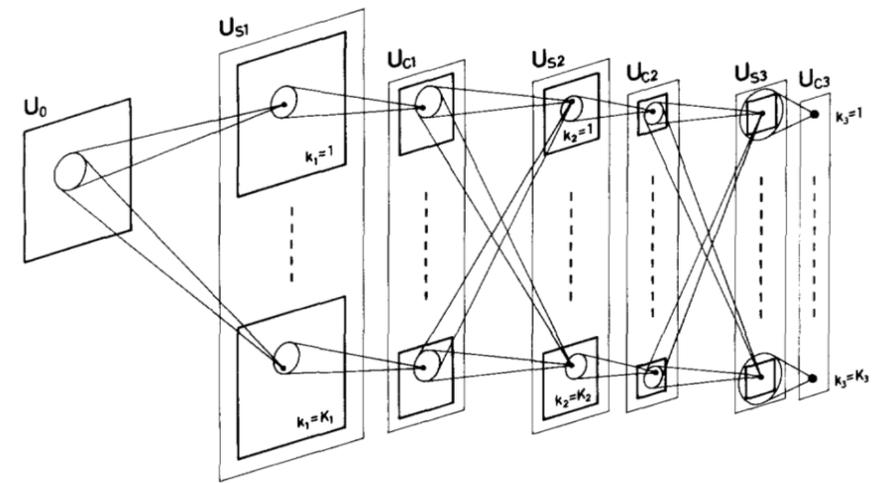
(1988) ● Explicit parallel implementations

(1998) ● LeCun's LeNet-5

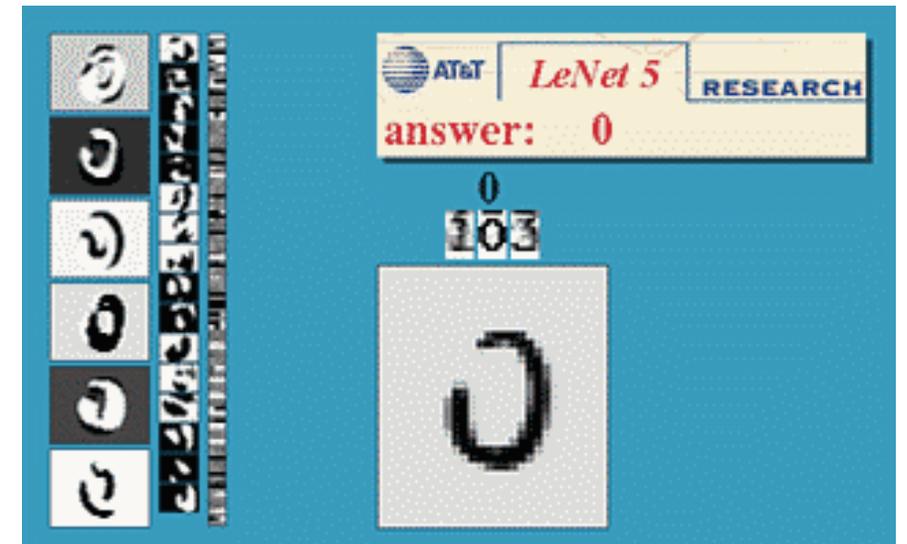
(2011) ● Ciresan's GPU Implementation

(2014) ● GoogLeNet

(2015) ● ResNet



Fukushima, Kunihiko, 'Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position,' Biological Cybernetics 36 (4): 193-202, 1980



LeNet 5 (1998), image source: <http://yann.lecun.com/exdb/lenet/>

DIVIDE AND CONQUER

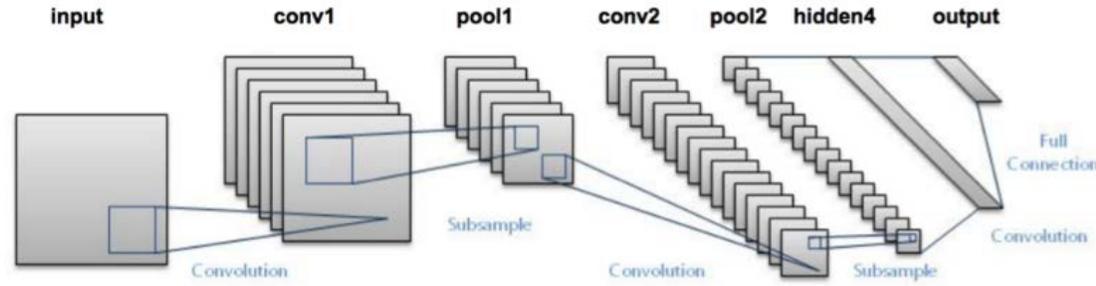
- Sorting training data is costly and time consuming
- Is there a way to automatically sort images?



HIERARCHIES OF CNNs

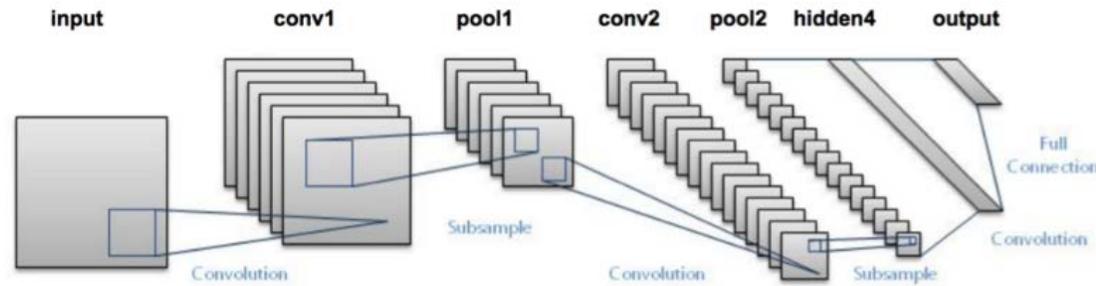


Image Database

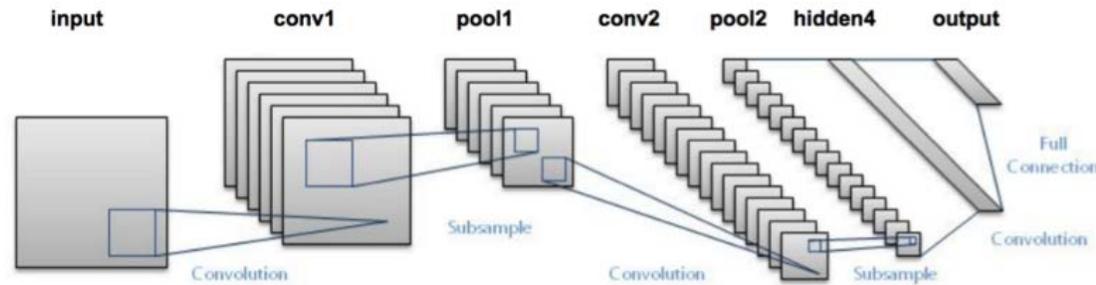


Sorted Images

- Front
- Back
- Left Side
- Right Side
- Other (discard)



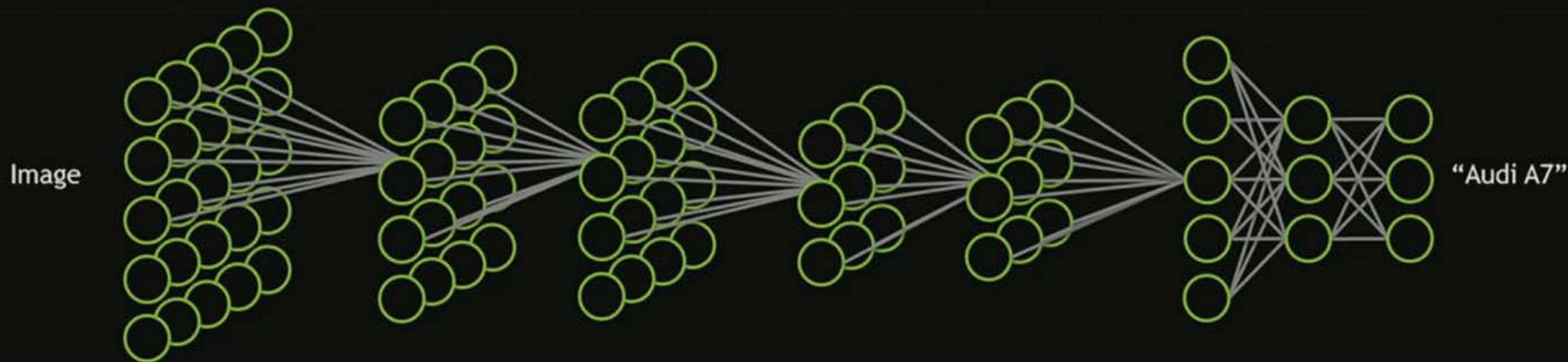
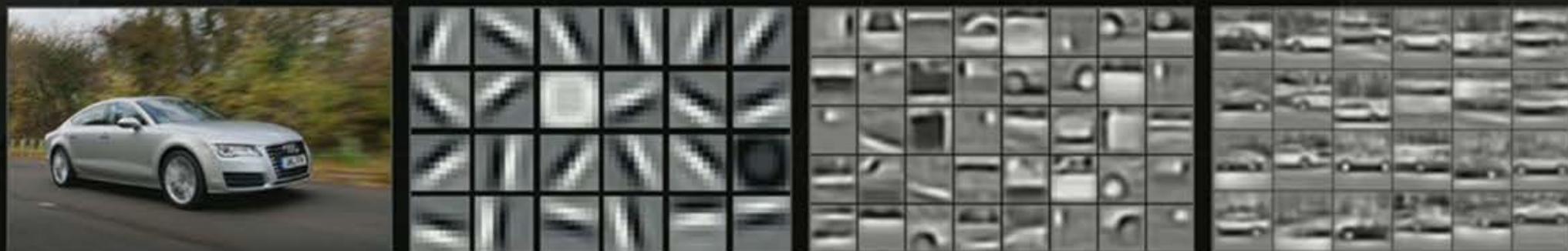
- No Damage
- Light Damage
- Medium Damage
- Heavy Damage**
- Severe Damage



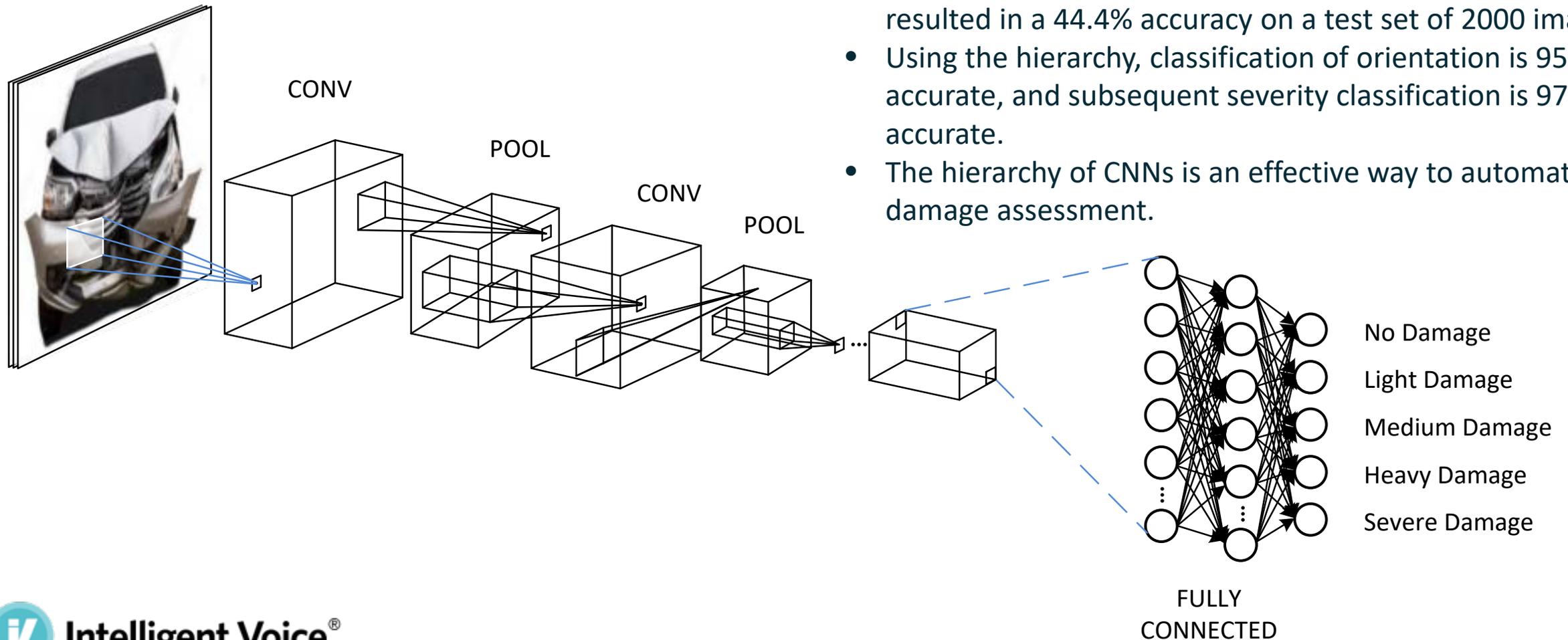
- No Damage
- Light Damage
- Medium Damage**
- Heavy Damage
- Severe Damage



HOW A DEEP NEURAL NETWORK SEES



SEVERITY CLASSIFICATION

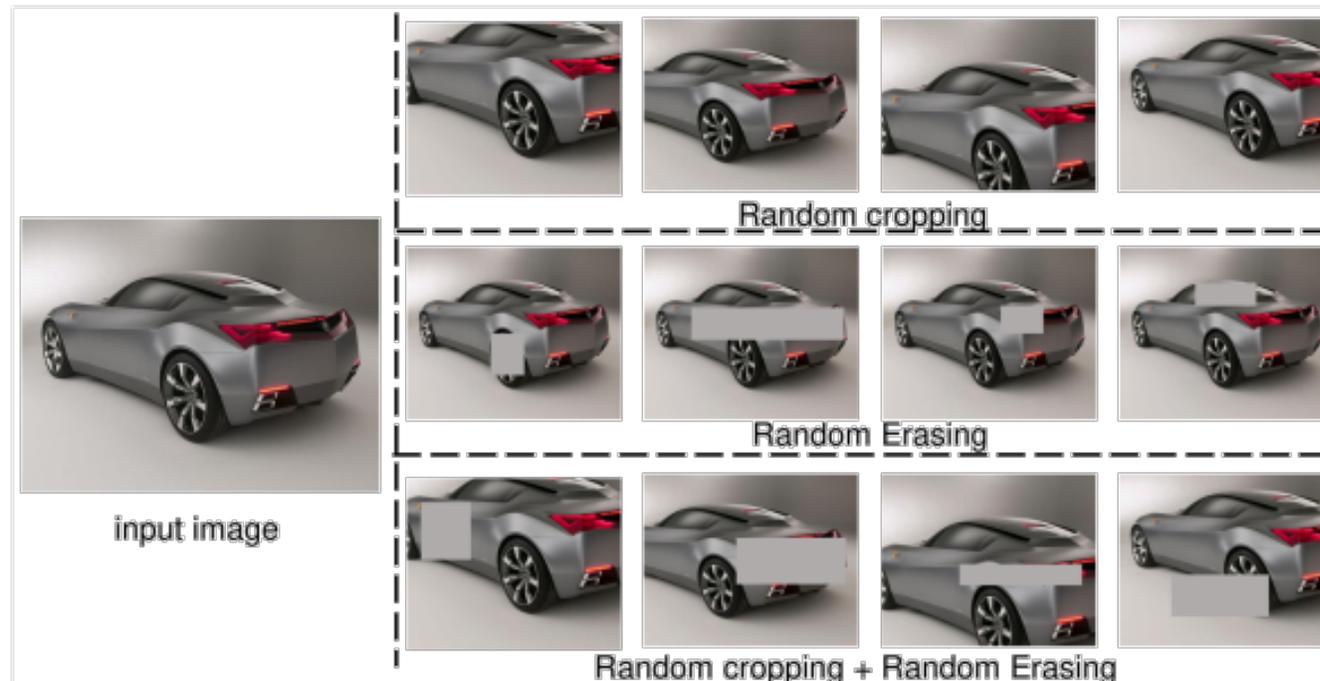


Preliminary Results

- Initial attempts to classify severity of damage with a CNN resulted in a 44.4% accuracy on a test set of 2000 images.
- Using the hierarchy, classification of orientation is 95.5% accurate, and subsequent severity classification is 97.0% accurate.
- The hierarchy of CNNs is an effective way to automate damage assessment.

DATA AUGMENTATION

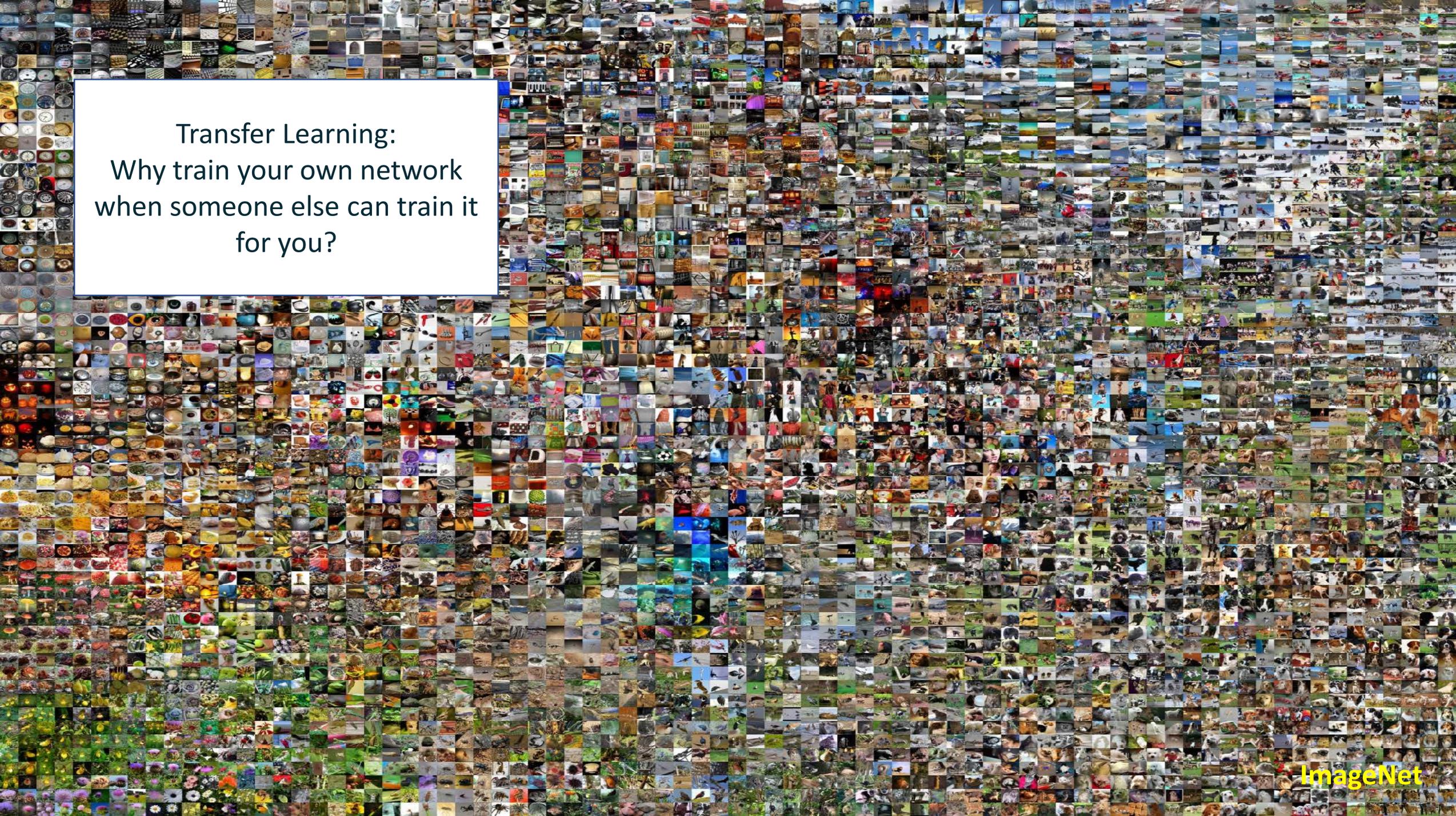
- How much data is needed?
- Importance of balanced data sets
- Augmentation can help – flips, crops etc
- Not just good for increasing data size but also for robustness



Random Erasing Data Augmentation

Zhun Zhong, Liang Zheng, Guoliang Kang, Shaozi Li, Yi Yang

arXiv



Transfer Learning:
Why train your own network
when someone else can train it
for you?

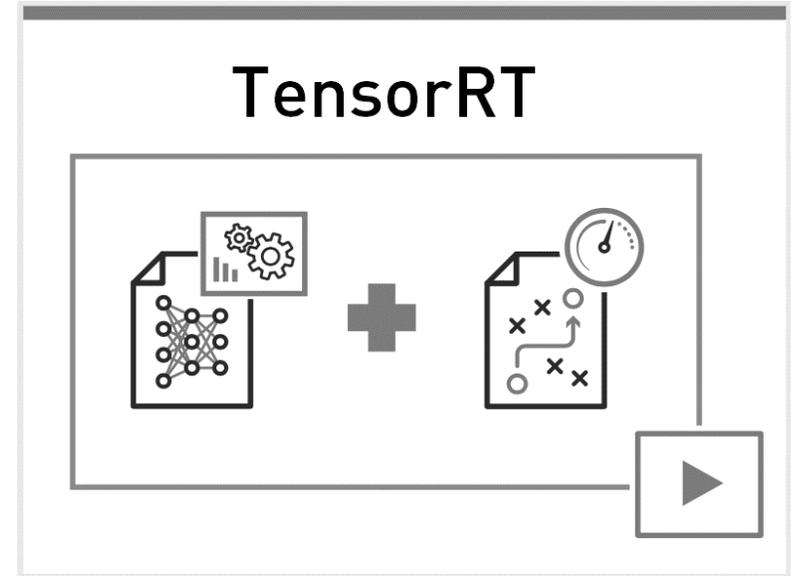
DOMAIN KNOWLEDGE

- Relating identified damage to car part numbers
- What about the parts under the surface?
- Estimating repair time
 - Complicated: to replace a grill, on some models requires taking out headlights
- Domain knowledge and access to historical data vital



ASSESSMENT ON THE GO

- Improved image capture
- Deployment on smart phones
- Mobile machine learning
- Optimised networks for faster inferencing





V2?

REGULATORY THOUGHTS

Article 22 GDPR

A black and white photograph of a person sitting on a brick wall. The person is wearing a grey t-shirt and dark jeans. They are holding a black Bible with "HOLY BIBLE" printed on the cover. A white wristband is visible on their left wrist. The background is a dark, out-of-focus interior space with a window.

WOULD I LIE TO YOU?



SPEECH ~~ANALYTICS~~ TECHNOLOGY



- ✔ Speaker Identification
- ✔ Source Separation
- ✔ Voice Activity Detection
- ✔ Speech Recognition
- ✔ Speech Enhancement
- ✔ Diarization
- ✔ Acoustic Modelling
- ✔ Spoken Dialogue Systems
- ✔ Speaker Recognition
- ✔ Language Modelling
- ✔ Language Recognition
- ✔ GPU Optimisation
- ✔ Privacy Preserving Speech Processing
- ✔ **Credibility Analysis**

WOULD I LIE TO YOU?

Problem: Insurance Fraud

The move to digital contact channels has removed the human element from insurance

£650m per year is paid by insurers as commission to aggregators

£3b per year in identified fraud across UK insurers with only a 43% detection rate

UK insurance industry **spends £200m per year on counter fraud** solutions

£1.7b of fraud remains undetected each year



AUDIENCE PARTICIPATION

HOW MANY PEOPLE LIE TO INSURANCE COMPANIES

8%

Drivers admit to giving incorrect details to insurers, according to study conducted by Consumer Intelligence.

-source: *The Telegraph* | 'Millions' lie on car insurance to cut costs by Andrew Oxlade 12 August 2013

20%

Of UK adults surveyed admitted to lying to their insurance company.

-source: *Poll of 2000 UK adults.*

- 29.3 % — [said it was] because they were unsure of the correct information or didn't understand the process from the start;
- 10 % — knowingly shared false info "because they were scared of the consequences of being totally truthful";
- 8 % — [said it was] because they "don't take the process seriously."

32%

In the UK, insurance customers were "more comfortable lying online than over the phone."

34%

would lie "to put a positive spin on a bad situation,"

1 in 10

would "lie about their weight," a pertinent question when it comes to getting some insurance policies.

- source: <http://hometownquotes.com/insurance-news/insurance/poll-reveals-many-people-will-lie-insurance-companies.html>

A survey of 2,115 American adults...conducted in February...shows that

16% of Americans believe it's acceptable to lie about smoking marijuana to receive lower life insurance rates.

...**one-in four-people** were willing to lie about under-the-table income

- source: *Insurance Journal* | Survey Shows Many Americans Fine with Lying to the IRS, or Their Insurer by [Don Jergler](#) 15 March 2016

[An] online survey asked 2,000 American drivers if they had ever supplied wrong information or left details out intentionally when applying for

coverage—and, for **34%** of the drivers surveyed, the answer was yes.

- 36.3% admitted they lied about their annual mileage
- 25.1% lied about who drove the vehicle
- 20.5% lied about past tickets or accidents
- 19.2% lied about gaps in their insurance coverage

- source: *InsuranceHotline.com* | Lies, Fibs, and Untruths: Survey Says Many Drivers Lie On Car Insurance Applications, 23 April 2014

SENTIMENT ANALYSIS



WE ARE LISTENING!

Solution:

Conversational AI

Understands your customer and agent behaviours to promote positive outcomes

Ensures your best agent represents the best of your brand on every call

Provides a digital safety net across your telephone interactions

Produces fastest commercially available voice transcription
200x real time

WHAT IS WRONG WITH THESE STATEMENTS?

- “Woke up at 7:30. Had a shower. Made breakfast and read the newspaper. At 8:30, drove to work.”
- “We should have done a better job.”
- “That’s their way of doing things.”
- “You’d better ask them.”
- Alleged robbery victim: “The man asked for my money.”
- “He told me not to look at him. He said he would shoot me if I screamed.”



INDICATIONS?

Pronouns:

Omission, Improper use, Higher rates of third person plural pronounced person plural pronouns

Complexity:

Parameters such as number of letters/syllables per word, higher word count, higher rate of pauses

Speaking verbs:

Strong tone (told, demanded, telling), soft tone (said, asked, stated, saying) – tone changes

Tempo:

Slow tempo (indicator of cognitive load), fast tempo (indicator of arousal and negative effects)

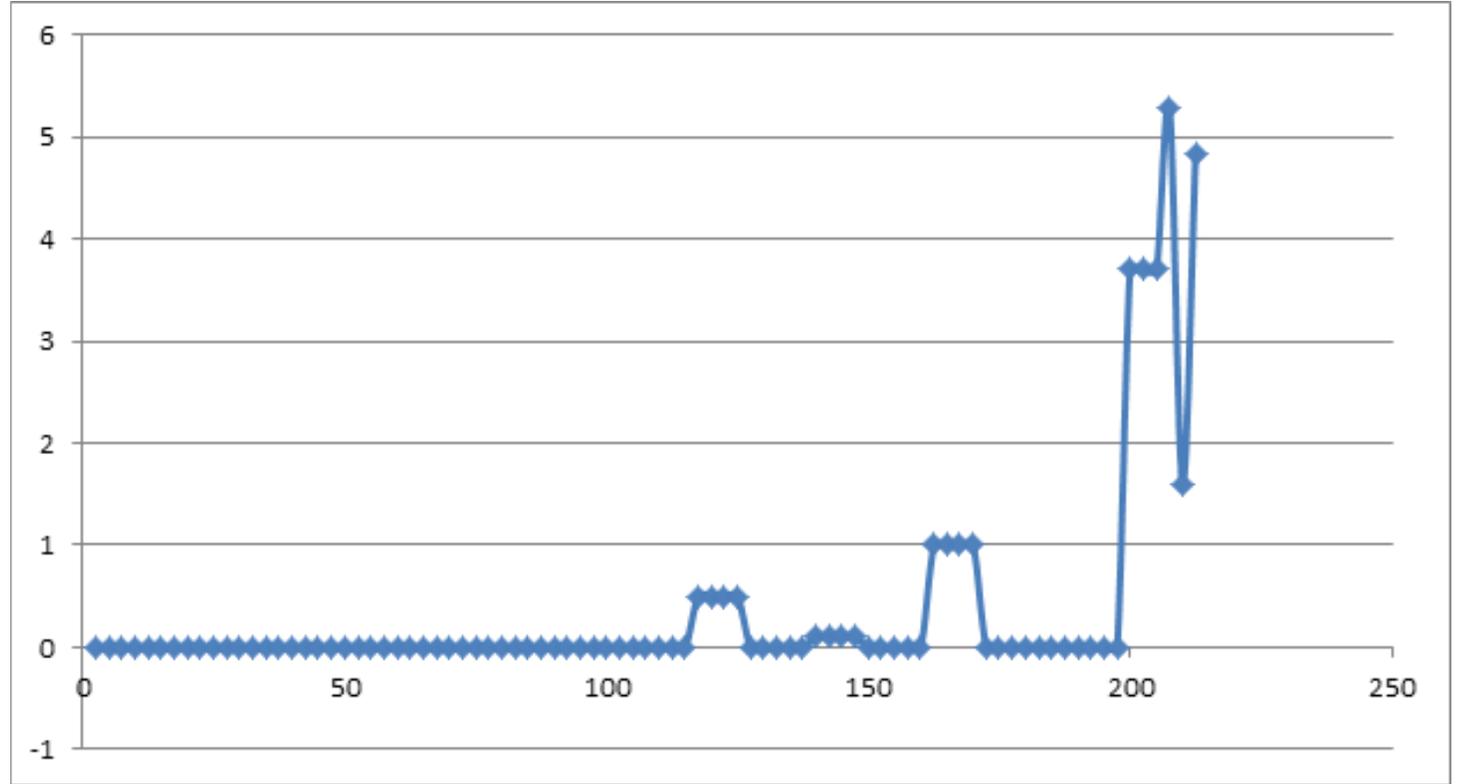
Pitch:

Higher pitch/lower voice quality at specific times are indications of fraudulent related utterances

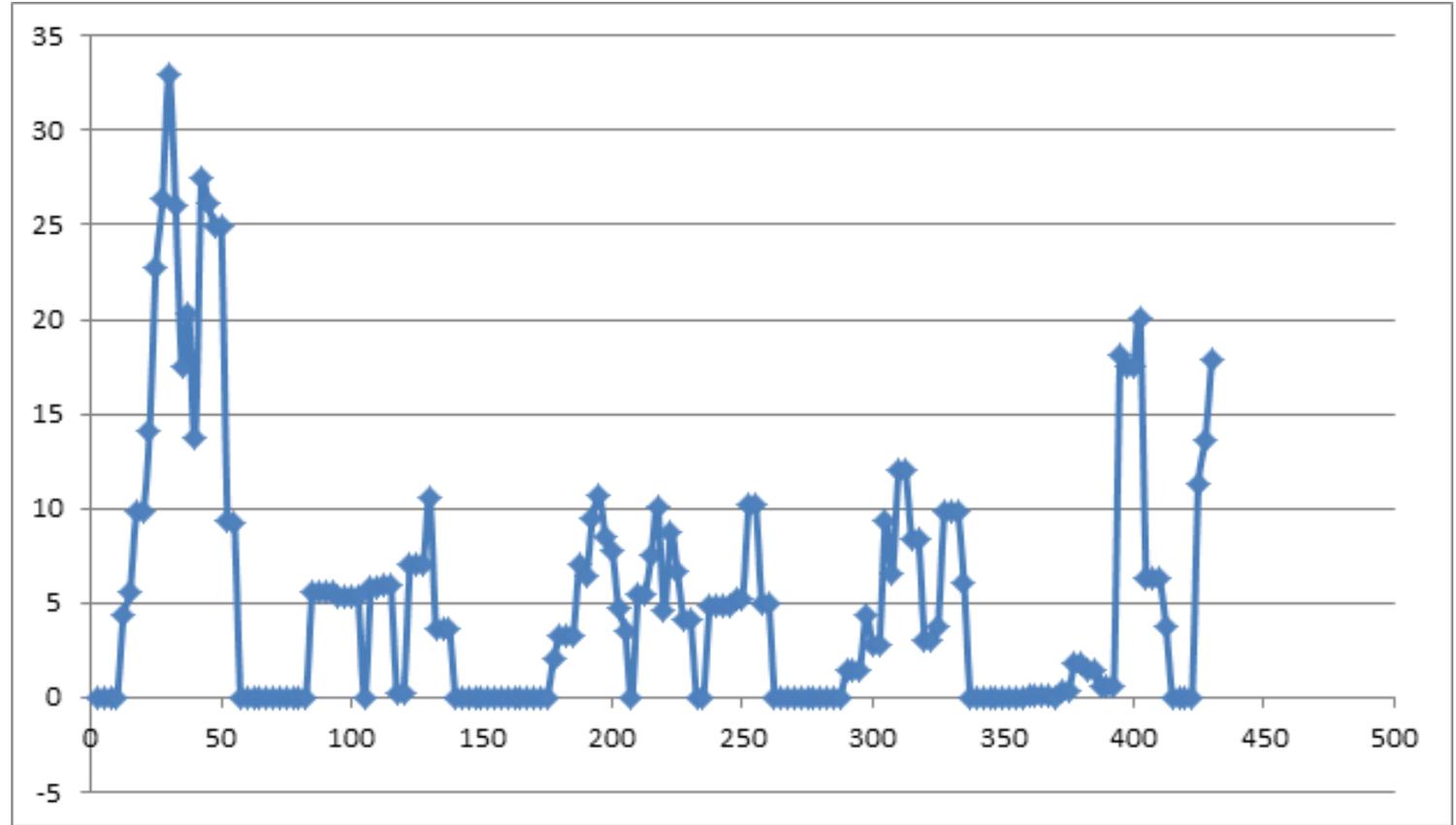
Specific Words:

Explainers (so, since therefore, because...)

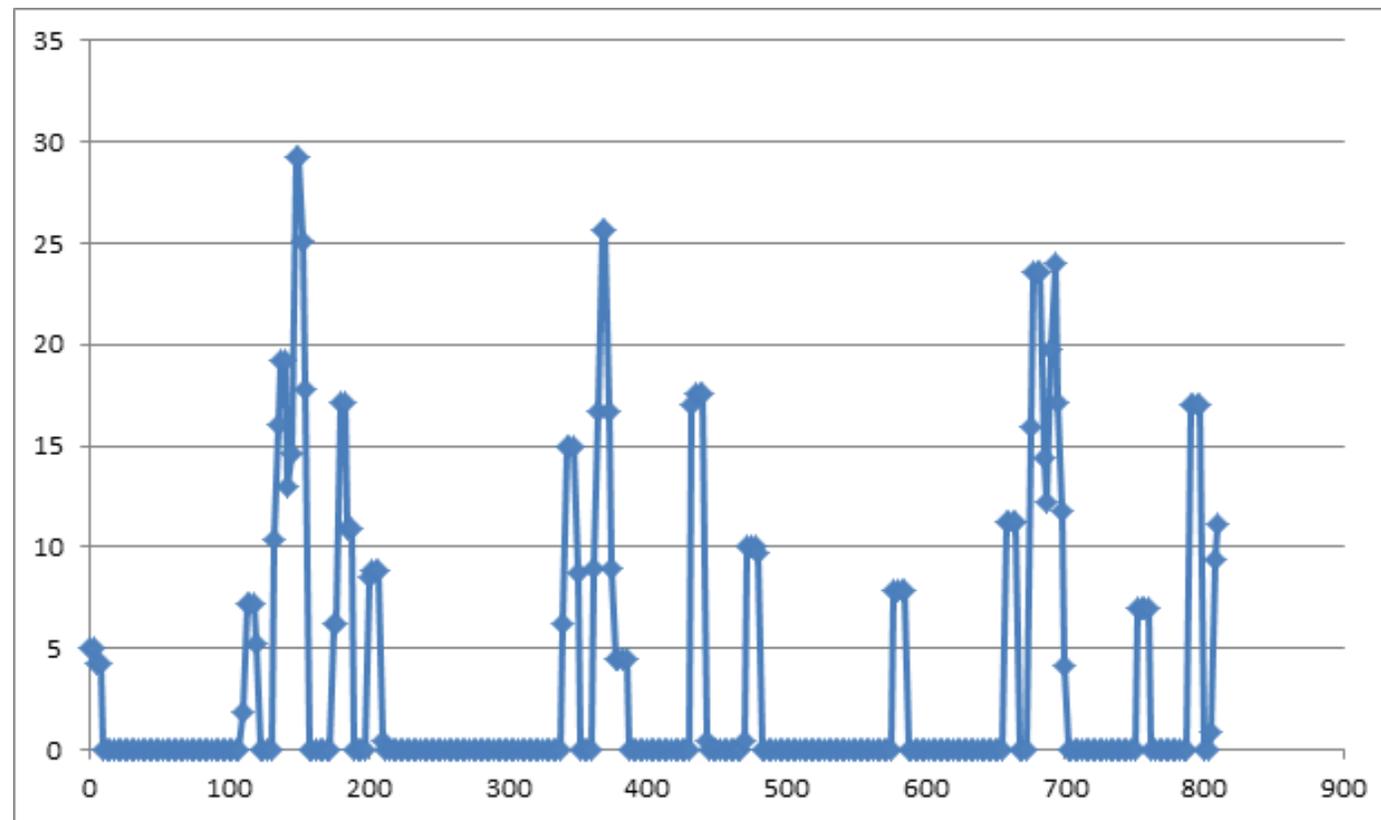
SCRIPTED CONVERSATION



ORDINARY CONVERSATION



EMOTIONAL CONVERSATION



CREDIBILITY ANALYSIS

Human Intelligence

Manual process highly skilled human

Very slow – very costly. Impossible to scale 3hours per 10 minutes

S: Um (2 seconds delay) I didn't really notice him until, well I seen him in Wetherspoon's and I'd seen him in there and then he was in the Eclipse as well um a very strange man, tattoo's all over his face, I'm not being judgemental but you know, you do notice things like that

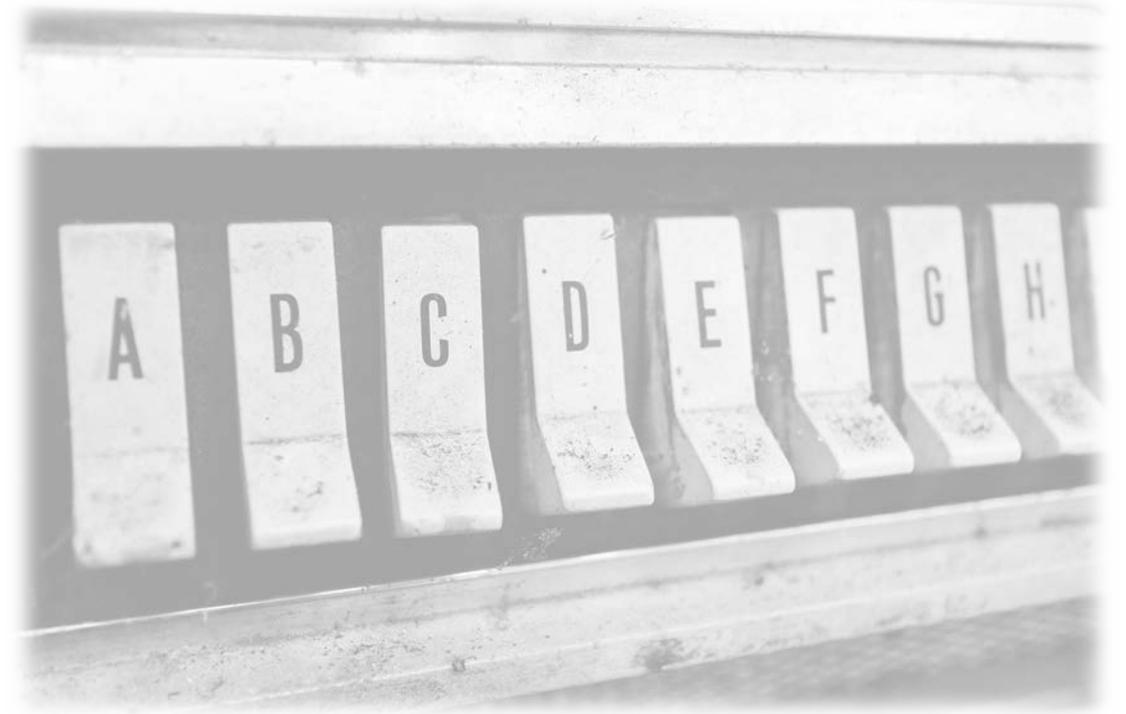
Pause
Negation
Broken Sentence
Repetition
Temporal Lacunae
Pause
Disparaging
Negation
But – to minimise what preceded it
"You know" not taking ownership. Wrong pronoun. This is proven as she has not mentioned it earlier and therefore may not be speaking from memory.

Handwritten annotations: "not really" with an arrow pointing to "you do notice things like that"; "Outball" with an arrow pointing to "you do notice things like that".

CREDIBILITY ANALYSIS

Machine Intelligence

- Analyse every call
- Faster than real time with no loss of accuracy
- Voice Recognition - Converts speech to text
- Deep learning language modelling
- Identify behavioural cues
- Measure credibility
- **Accurate – Scalable – Cost effective**



CREDIBILITY NETWORK



Voice Activity Detection



GPU-accelerated RNN-based Speech to Text

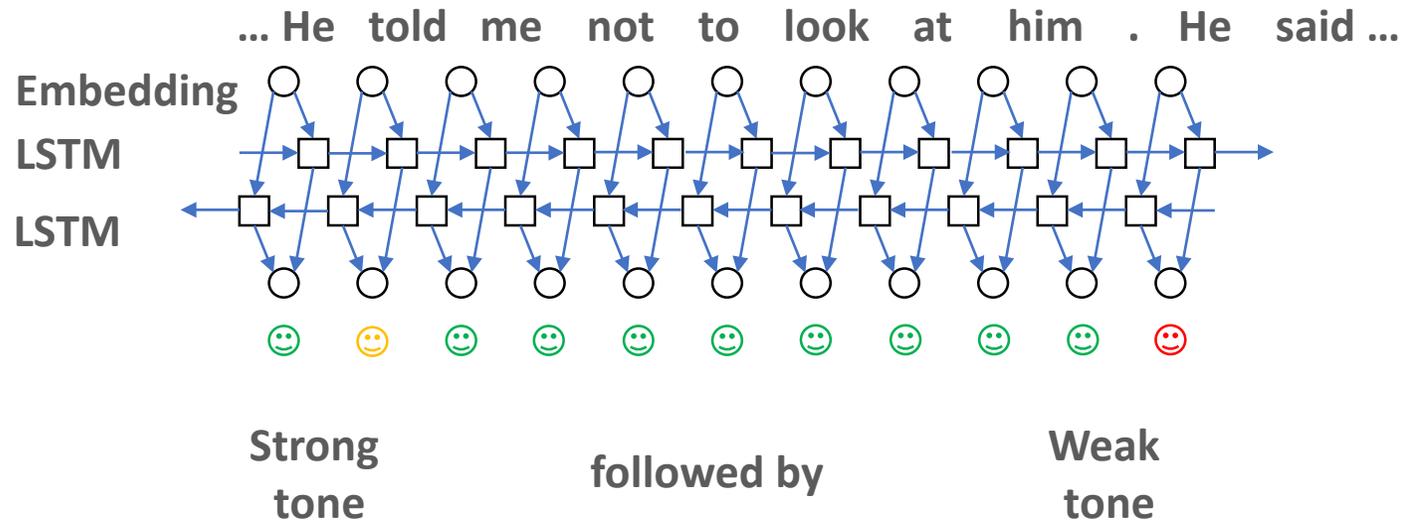


i-vector diarization



INTERVIEWER
What happened next?

CALLER
He told me not to look at him. He said he would shoot me if...



- Inspired by recurrent networks for named entity recognition and part of speech tagging
- We can use bi-directional recurrent networks to attach credibility tags to the speech transcription
- Bi-directionality is important for context
- Network can tag explainers, changes in tone, pronouns etc.

CREDIBILITY ANALYSIS

Machine Intelligence

strennus ,
q+qwB6ALRvmbXqSSscv1tw ;
2016-08-08 11:51:01

cm_vague.wav (01:08) strennus import75



SPEAKER 2:

And So So What Was The Overall Cost Of The The Chain

SPEAKER 3:

Three Thousand

SPEAKER 2:

How Much Three Thousand Did You Say

SPEAKER 3:

Yeah

SPEAKER 2:

O.k. Sure O.k.

SPEAKER 3:

I've Got The Receipt To Prove It Everything

SPEAKER 2:

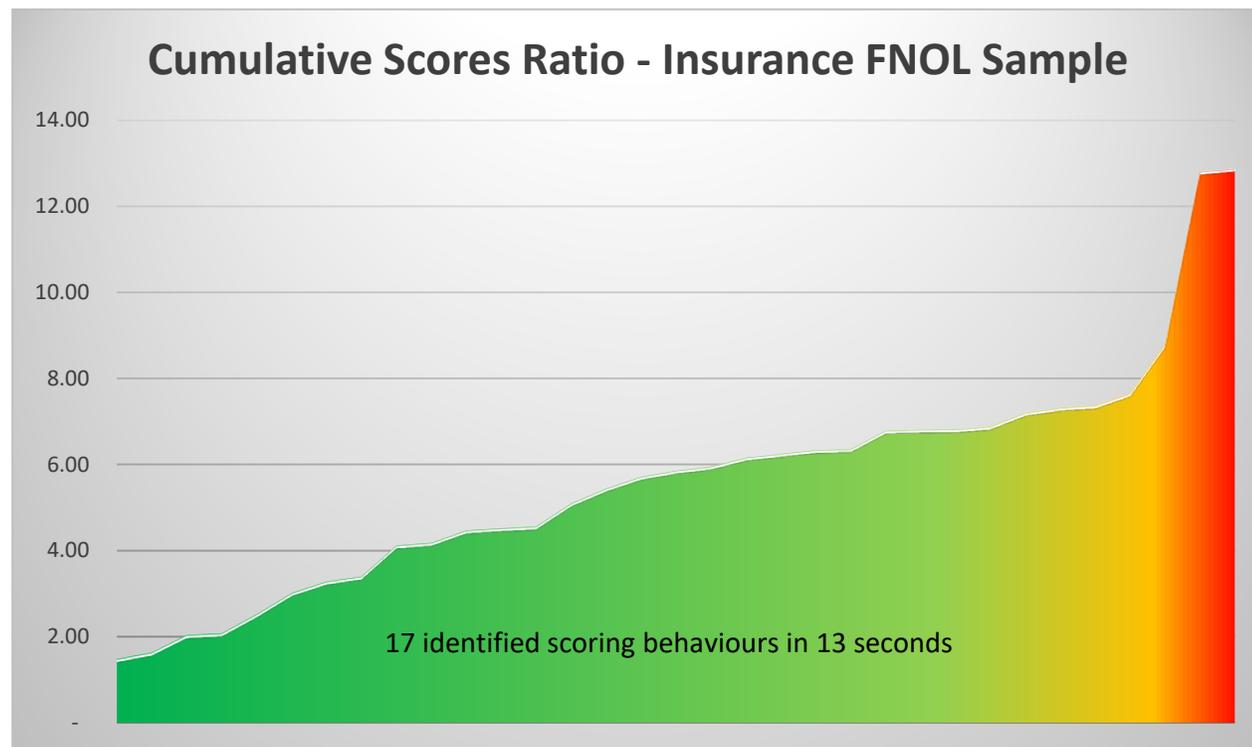
OK Sure And Sorry Of What It Catches What Was The Name Of The Jewellers You Purchased From.

SPEAKER 3:

God You Know What Mate I Have No I Couldn't. I Could Not Tell You Mate God's Honest Truth I Could Not Tell You The Name Of The Jewellers As I Could Tell You Where It Is I Know Exactly Where It Is

SPEAKER 2:

Where Is It.



“God you know what mate, I have no, I couldn't, I could not tell you mate. God's honest truth, I could not tell you the name of the jewellers, I could tell you where it is, I know exactly where it is.”

HOW CAN WE HELP?



- ✔ Live Alerting
- ✔ Trend Analysis
- ✔ Access every spoken word
- ✔ Proactive Staff Monitoring
- ✔ Know your customer
- ✔ Compliance Assurance
- ✔ Business process adherence
- ✔ Visibility
- ✔ Complaints Intervention
- ✔ Customer Experience Monitoring
- ✔ Contact Centre
- ✔ Predictive Analytics
- ✔ Human Resources
- ✔ QA

CONCLUSION

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