

INTRODUCTION

The team & the speaker



Investments AI

- Keywords: Machine Learning, AI-first, Disruptive Innovations.
- Provide end-to-end AI-first solution/product/platform
- Premium sponsor of **NIPS** and **ICML** since 2016

Speaker

Director, Statistical Machine Learning, AIG

- DPhil in Statistics (Machine Learning), University of Oxford
- MSc in Applied Statistics, University of Oxford
- BSc in Mathematics with Statistics, University of Bristol

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Looking for disruptive opportunities

Overview of AI

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OVERVIEW OF AI

Why AI?

“Over time, we will move from mobile-first to an AI-first world”

Sundar Pichai, CEO of Google

“Our responsibility is to have AI augment the human ingenuity and the human opportunity”

Satya Nadella, CEO of Microsoft

“I believe that at the end of the century, general educated opinion will have altered so much that one will be able to speak of machines thinking without expecting to be contradicted”

Alan Turing, Father of General-Purpose Computer

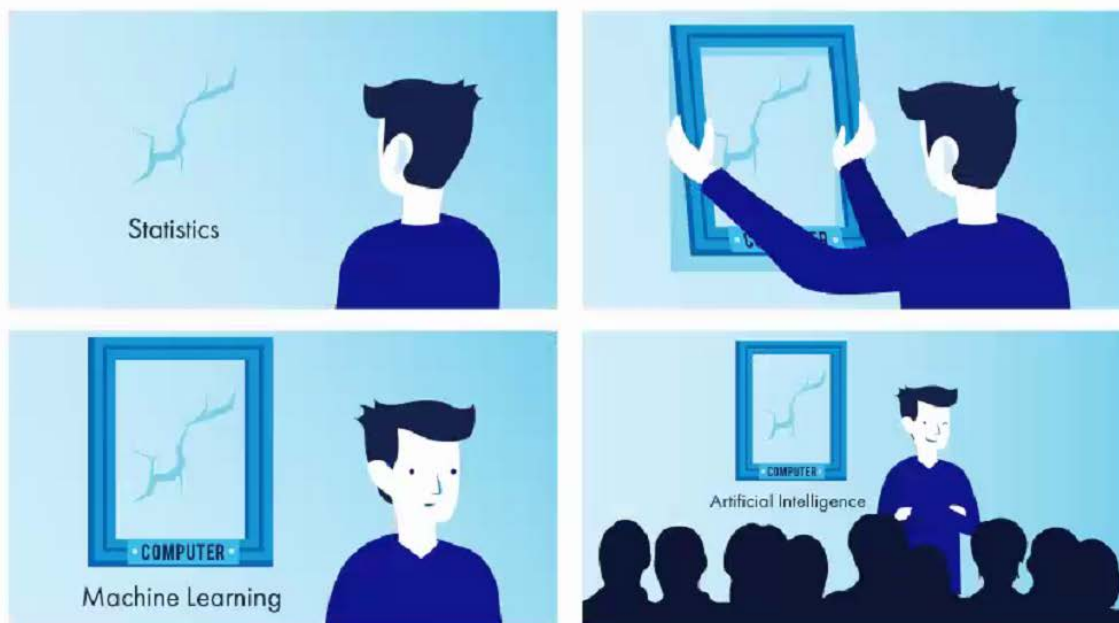
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What is AI?



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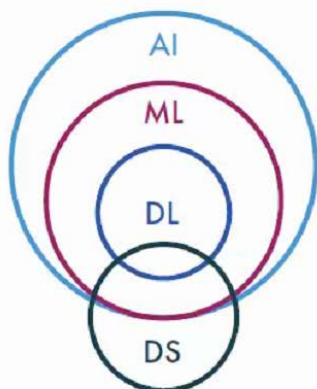


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AI = statistics -> Machine Learning -> AI

Glossary Term

Some relevant terminologies have been misused and remained controversial



Artificial Intelligence

- A flexible rational agent that perceives its environment and takes actions that maximise its chance of success at some goal
- Mimic "cognitive" functions as humans to "learn" and "solve problem"
- It does not have to involve learning or induction at all, e.g. "a mousetrap"

Deep Learning

- A sub-set of machine learning that uses multi-layered neural networks to learn
- Mainly focuses on computer vision, speech and text recognition
- Foundation for driverless car

Machine Learning

- Internal and external sources
- A sub-field of AI
- Combination of science and engineering to make machines "learn" from data
- Inductive component is compulsory



Data Science

- Interdisciplinary: statistics, mathematics, computer science, and business
- Collect, organise, analyse large amount of data to generate actionable insights
- Data could be structured and unstructured up to very complex structure
- Not necessary to mimic/simulate human intelligence

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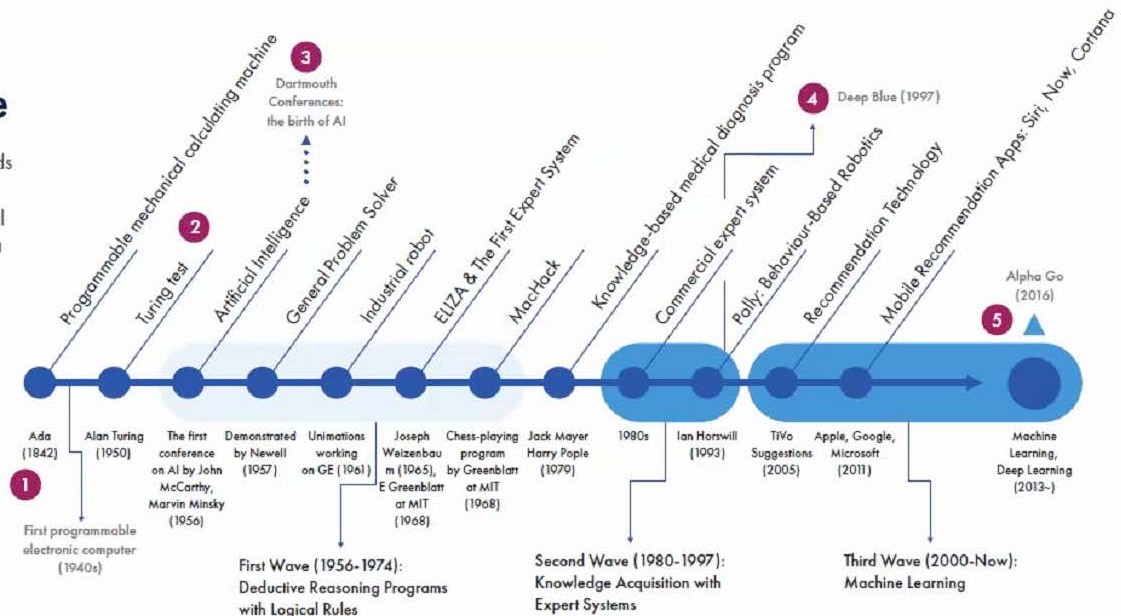
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More information can be found at AIG AI Contact Page:

<https://contact.aig.net/pc/scn/Pages/Science%20Landing%20Page.aspx>

AI Timeline

Ancient AI started thousands of years ago – mainly are associated with mechanical engineering for automation



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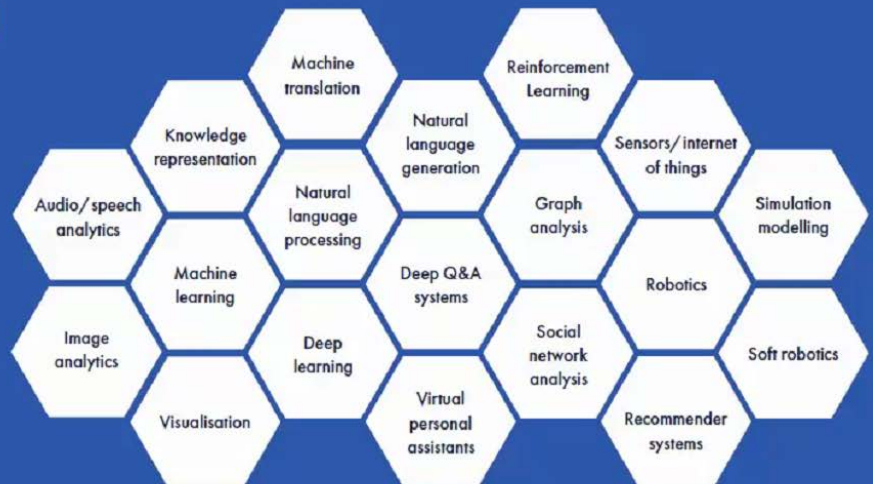
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Third wave starting 2000 and ending now – Nowadays AI = Deep Learning

The Current Wave of AI

Non-exhaustive list of components of AI



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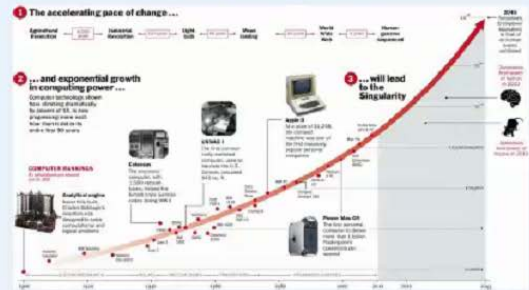
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Four Key Drivers to The Current Wave of AI

Data¹



Computing Power²



Algorithms³



AND Investment!!!

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Exponential growth of data, computing power and algorithms

Data Explosions



"Every 2 days we create as much information as we did up to 2003."

Eric Schmidt, Google CEO



If the Digital Universe were represented by the memory in a stack of tablets, in 2013 it would have stretched two-thirds the way to the Moon*

By 2020, there would be 6.6 stacks from the Earth to the Moon*

"Amount of data doubles every two years. By 2020, there will be 44 zettabytes of data available, which is equal to 44,000,000,000,000,000,000,000 bytes!!!"

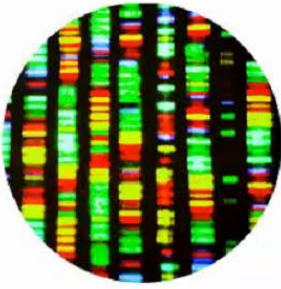
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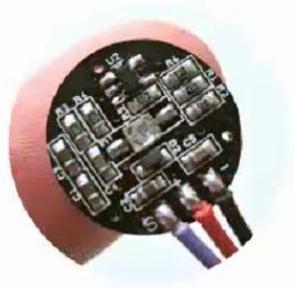
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New Data Sources Available to Fuel Insight Creation



Genome sequencing

Massive decreases in cost of genome sequencing, from \$96M in 2001 to \$4K today



World of sensors

Trillions of internet-connected sensors collecting and sharing data to improve insight



Narrative Science

Natural language written by machines to make data simple and easier to understand

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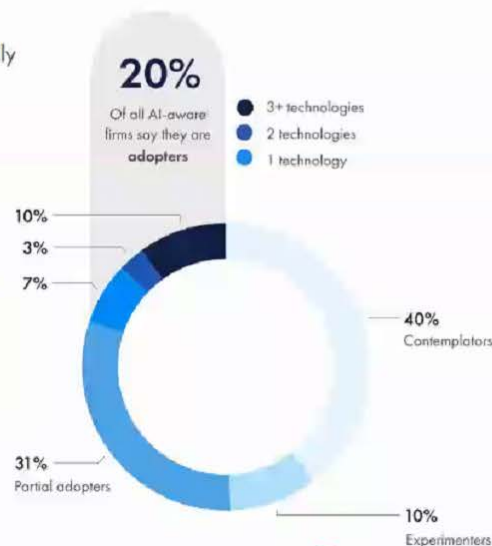
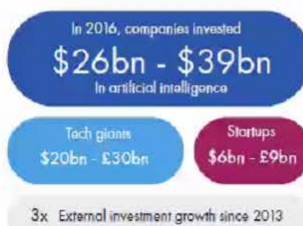
OVERVIEW OF AI

Investments in AI

US-based companies absorbed 66% of all AI investment in 2016, followed by China with 17%

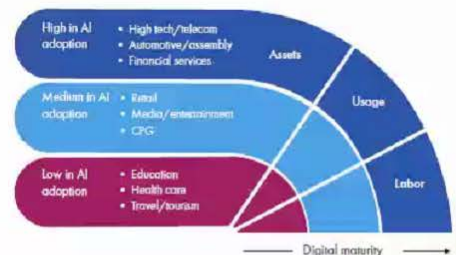
The current AI wave is poised to finally break through

Investment in AI is growing at a high rate, but adoption in 2017 remains low:



How companies are adopting AI

Investment in AI is growing at a high rate, but adoption in 2017 remains low



Six characteristics of early AI adopters



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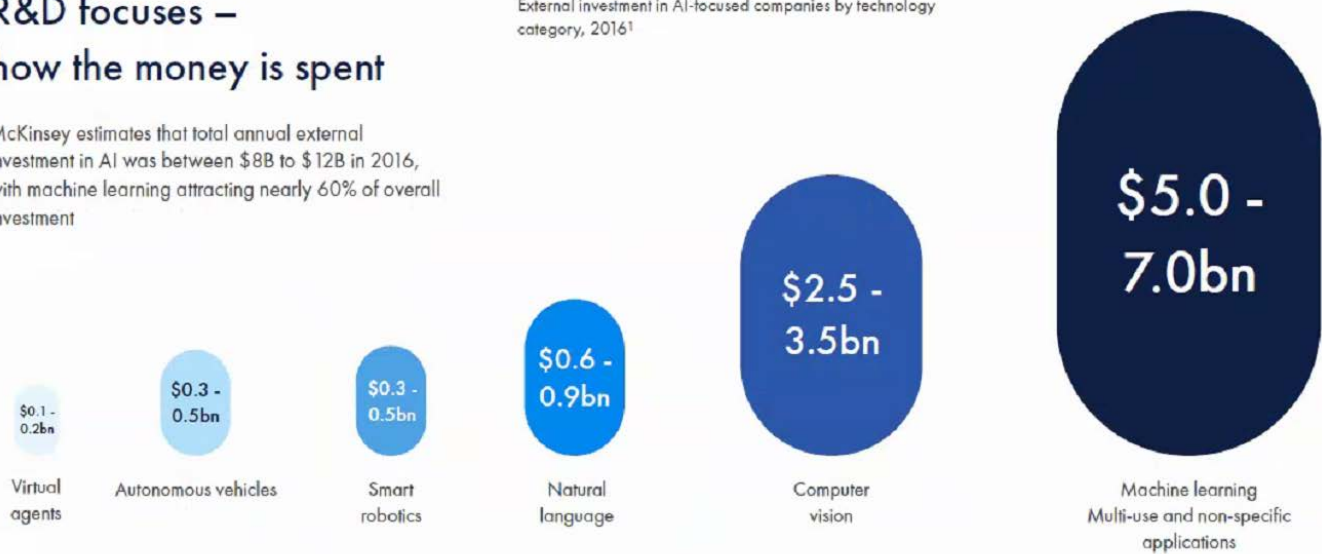
R&D focuses – how the money is spent

McKinsey estimates that total annual external investment in AI was between \$8B to \$12B in 2016, with machine learning attracting nearly 60% of overall investment

VIEWING PRESENTATION ACTIONS

Machine learning received the most investment, although boundaries between technologies are not clear-cut

External investment in AI-focused companies by technology category, 2016¹



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¹ Estimates consist of public "VC" investment in AI-focused companies. PE investment in AI-related companies and publicly corporate investment in AI-related companies is not included. Data available in the McKinsey Quarterly database.

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AI IN FINANCE

Future AI demand

Financial Services are leading the digitalisation, supporting digital assets, exposure to AI in workforce; but relatively weak at AI spend, and AI resources per worker

AI adoption is occurring faster in more digitised sectors and across the value chain



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Financial services' current leading role in AI adoption

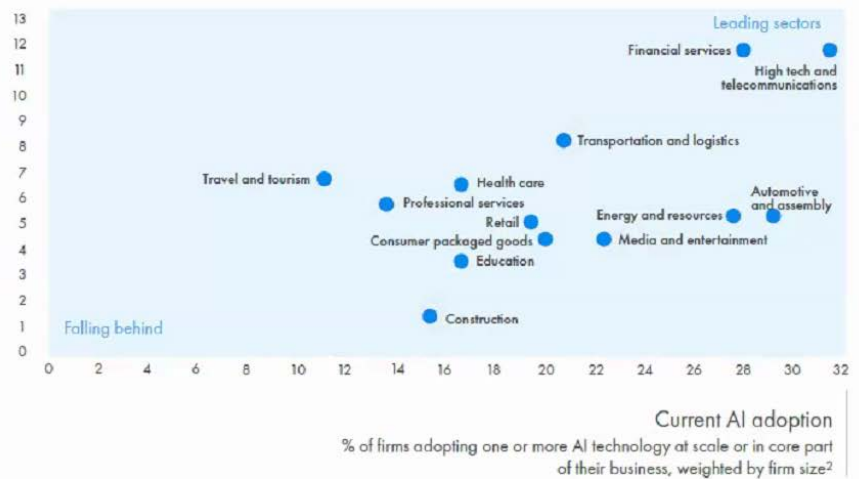
The next three years' demand for AI adoption in Financial Services will be higher than High Tech. The competition for patents and IP is accelerating

The benefits of AI in Financial Services industry is pretty clear. For example, the improved accuracy and speed in AI-optimised fraud-detection systems standing alone is forecasted to be a \$3B market in 2020.

Sectors leading in AI adoption today also intend to grow their investment the most

Future AI demand trajectory¹

Average estimated % change in AI spending, next 3 years, weighted by firm size²



Investments/Finance is catching up on AI demand

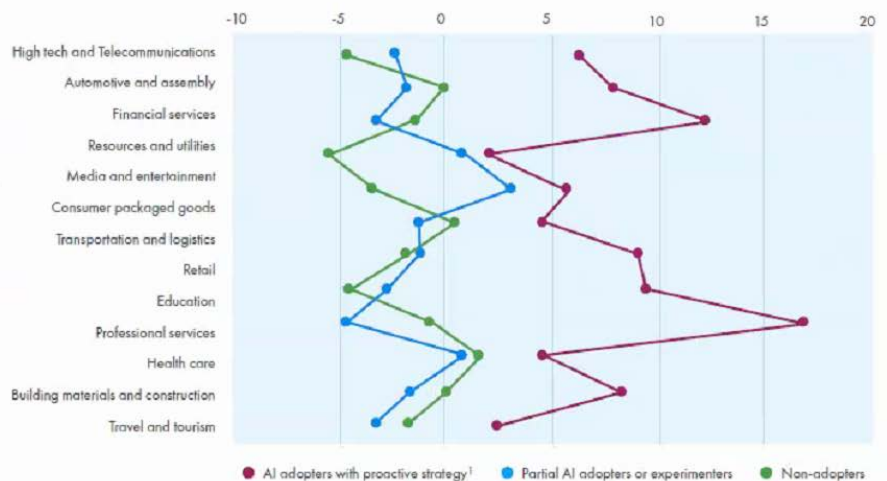
Profit margin improvement due to AI adoption

Healthcare, Financial Services, and Professional Services are seeing the greatest increase in the profit margins as a result of AI adoption

AI adopters with a proactive strategy have significantly higher profit margins

Self-reported current profit margin²

Difference from industry average (unweighted) (percentage points)



¹ Firms that are big data and cloud services users and report their strategic posture towards AI to be: "Disrupting our industry using AI technology is at the core of the strategy"; "We have changed our longer-term corporate strategy to address the AI threat or opportunity disruption," or "We have developed a coordinated plan to respond to the AI threat or opportunity but have not changed our longer-term corporate strategy."

² Operating profit margin for the most recent year as reported by firms as a percentage of revenue, excluding one-time gains and losses, and financial engineering.

Source: McKinsey Global Institute

No differences between non-adapters and partial adapters -

AI's booming in financial industry

Buzzword or reality?

Silicon Valley Hedge Fund Takes On Wall Street With AI Trader

Sentient Technologies won't disclose its performance, but is being closely watched by the finance and artificial intelligence communities.



Expected explosive interest in AI in Finance

AI in finance – player landscape

Players across different market segmentations have stepped into AI



What is Insurance?

At a high level, excellence in insurance can be associated to success is in its key pillars



The Nine Killer Applications of Digital Technology in General Insurance



Deloitte – Cyber risk can be huge

The Current State of AI

Computers can see, read, listen, talk and learn strategy – due to advances in Machine Learning / Deep Learning.



General Predictive Modelling



Natural Language Processing



Computer Vision



Reinforcement Learning



Conversational AI

Most mature: genreal predictive modelling

AI IN INSURANCE

The Journey of Science

- Distribution (SubPro, OppMap, X-sell, Longevity)
- Technical Pricing (inc AQI)
- Broker relationship (BQI)
- Anti-fraud
- Claim & Reserving
- Consumer Loyalty

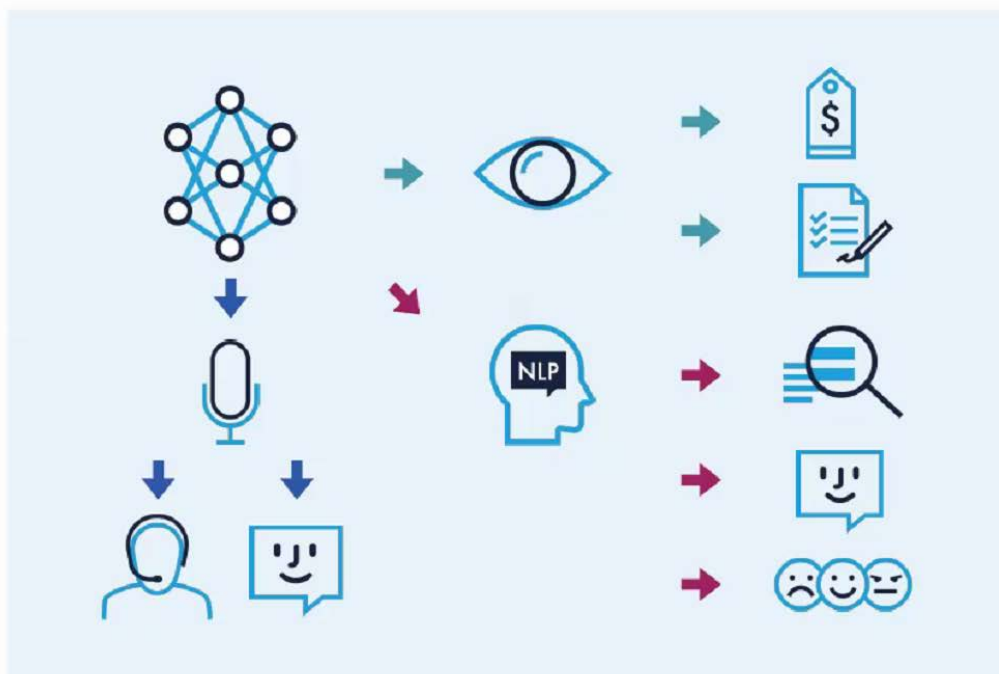


- [Investments AI](#)
- Auto Damage Detection
- NLP
- Computer Vision
- Behaviour Science
- Sensors and IoT
- Shared Economy

- Skyhook (cloud-centric system)
- Donut (AI UW Platform)
- Claim notes automation
- Human Conditions

Consultancy – Advise business on AI R&D AWS centric

Deep Learning Practices in Insurance

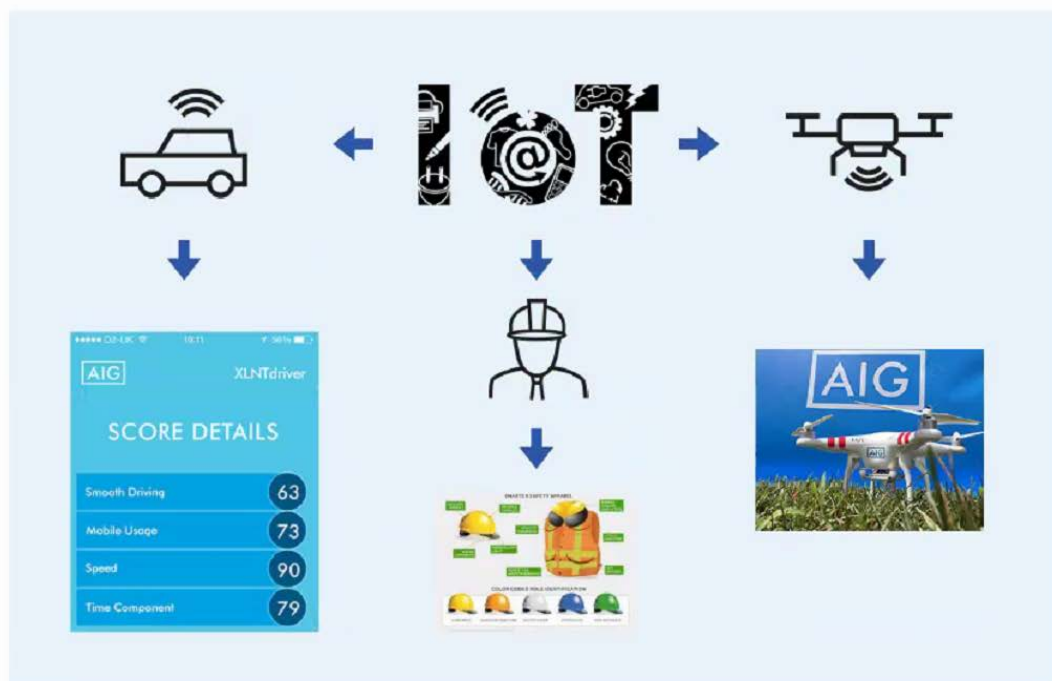


“Sharp Eye” scan your home to determine what needs be insured

Finance text data: contracts, claims, coverages – sentiments

Internet of Things

The main source of Big Data



Research

NIPS, 2018

Benchmarking Deep Sequential Models on
Volatility Predictions for Financial Time Series

ICASSP, 2019

ICML, 2017

NIPS, 2017

STRUCTURAL VARIATIONAL BAYES NETWORKS

Inferential Tweedie Componential Poisson Mixture

Adversarial Variational Inference for Tweed's Compound Poisson Models

Neuro (American Health) Inc. has made its mark on the American market by making its own, unique, complete line of products available to the general public. The company's line of light bulbs, for example, is a real success story. The company's line of light bulbs is a real success story. The company's line of light bulbs is a real success story.

Introduction

of continuous random variables, with the number of observations determined by a Poisson-distributed random variable. The model is fitted to the data by maximizing the likelihood function, and the model is evaluated using the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). The model is compared to a null model, and the results are compared to the results of a Monte Carlo simulation. The model is also compared to a model with a fixed number of observations, and the results are compared to the results of a Monte Carlo simulation. The model is also compared to a model with a fixed number of observations, and the results are compared to the results of a Monte Carlo simulation.

To date, most studies of Drosophila feeding are concerned with the acquisition of food (e.g. *Wagman and Ragsdale, 1981*). However, the feeding system is also involved in the control of food intake (e.g. *Wagman and Ragsdale, 1981*). In this study, we have examined the role of the feeding system in the control of food intake. We have found that the feeding system is involved in the control of food intake in a manner that is consistent with the role of the feeding system in the control of food intake in other animals (e.g. *Wagman and Ragsdale, 1981*). We have also found that the feeding system is involved in the control of food intake in a manner that is consistent with the role of the feeding system in the control of food intake in other animals (e.g. *Wagman and Ragsdale, 1981*).

Yuehong Yang, Bei Cao, Rong-Ming Zhou, Yueshan Fan
Department of Management Science, Tsinghua University, Beijing, China

[illegible]

The Brazilian Corporate Ethics Institute (Instituto Brasileiro de Ética e Governança Empresarial) has been instrumental in the development of an ethics model in the Brazilian business environment. The Institute was created in 1996 by a group of professionals from the business community, aimed at the growing tendency in the state to impose requirements of formalization of ethics in the organizations. The Institute's main goal is to disseminate and promote the adoption of the business ethics practices, and the Institute's first initiative of this kind has been presented as a challenge to the business community in Brazil, in the study to be titled the Brazilian Business Ethics Institute's Code of Ethics and Values (Instituto Brasileiro de Ética e Governança Empresarial's Código de Ética e Valores). The code is being progressively implemented, under the Institute's leadership, and includes the creation of products, implementation of courses and seminars, and the organization has had a number of Brazilian Business Ethics Institute's chapters in various cities of the country. The Institute's code is not intended to be a formal standard, but a guide to be used. The code proposed includes the highest standards for the best companies of the country, as well as the minimum standards required. It is an effort to contribute to the business environment in Brazil, by disseminating a code of ethics, and to the business community, by offering a cultural adaptation of the corporate literature.

[illegible]

Journal of International Strategic Management

Fig. 4 Growth results of *Pseudomonas* and other bacteria.

[illegible]

Abstract: A comparison of measurements for the first two stages of a double-slit system in which the particles are emitted within a limited range. An experiment is described in which the particles are emitted within a limited range. An experiment is described in which the particles are emitted within a limited range.

[illegible]

unconstrained subjects to a study of the genetic structure of *Helicoverpa* such as *Helicoverpa virescens*, which has been the dominant pest of cotton in the Americas (Holt 1992). In aquaculture hatcheries, complex, uncontrolled systems to enhance diversity of the genetic stock are used, for example, to improve the growth rate. The first of these is the performance of large numbers of crosses. Males are collected, identified and related to females in the same or other hatcheries before mating. Making the crosses usually requires extensive field studies, and the genetic structure is determined on the basis of molecular markers and/or data on the matings (Saghai-Maroof et al. 1984).

Secondly, *in vitro* fertilization is followed by *in vitro* selection of *in vitro* embryos (Holt 1992). This is done in order to select for desirable traits, such as growth rate, and to avoid the problems of inbreeding. Embryos are selected on the basis of their size and are cultured in the laboratory (Saghai-Maroof et al. 1984).

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Tweedie Distribution

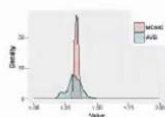
Variational Inference

Why we need it?

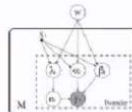
Tweedie Compound Poisson models are heavily used for modelling non-negative continuous data with a discrete probability spike at zero. An important practice is the modelling of the aggregate claim loss for insurance policies in actuarial science. However, the intractable density function and the unknown variance function have presented considerable challenges for Tweedie regression models.

We tackle the Bayesian Tweedie regression problem via a Variational approach. In particular, we empower the posterior approximation by an implicit model trained in the adversarial setting, introduce the hyper prior by making the parameters of the prior distribution trainable, and integrate out one local latent variable in Tweedie model to reduce the variance.

Our method is evaluated on the application of predicting the losses for auto insurance policies. Results show that the proposed method enjoys a state-of-the-art performance among traditional inference methods, while having a richer estimation of the variance function.



Posterior distribution of the index parameter P for Adversarial Variational Bayes (AVB) is much more flexible than the distribution learned using MCMC method. This allows to more accurately model the loss distribution.



Model learns a distribution of global weights W , which combined with the client features X to infer the Tweedie distribution parameters λ , α and β . Then loss Y can be sampled to obtain the average and all quantiles.

Research Case I – Bayesian Tweedie

Results: AVB method shows state-of-the-art performance, even compared with the TDBoost method which is considered to be the strongest.

Table 1: The pairwise Gini index comparison with standard error based on 20 random splits

Baseline / Model	GLM	PQL	Laplace	AGQ	MCMC	TDBoost	AVB
GLM	/	-2.97 _{6.28}	1.75 _{5.68}	1.75 _{5.68}	-15.02 _{7.06}	1.61 _{6.32}	9.84 _{5.80}
PQL	7.37 _{5.67}	/	7.50 _{6.26}	7.50 _{5.72}	6.73 _{5.95}	0.81 _{6.22}	9.02 _{6.07}
Laplace	2.10 _{4.52}	-1.00 _{5.94}	/	8.84 _{5.36}	4.00 _{4.61}	21.45 _{4.84}	20.61 _{4.54}
AGQ	2.10 _{4.52}	-1.00 _{5.94}	8.84 _{5.36}	/	4.00 _{4.61}	21.45 _{4.84}	20.61 _{4.54}
MCMC	14.75 _{6.80}	-1.06 _{6.41}	3.12 _{5.99}	3.12 _{5.99}	/	7.82 _{5.83}	11.88 _{5.50}
TDBoost	17.52 _{4.80}	17.08 _{5.36}	19.30 _{5.19}	19.30 _{5.19}	11.61 _{4.58}	/	20.30 _{4.97}
AVB	-0.17 _{4.70}	0.04 _{9.62}	3.41 _{4.94}	3.41 _{4.94}	0.86 _{4.62}	11.49 _{4.93}	/

We evaluate our method by predicting losses for auto insurance policies. Dataset properties:

- 10,296 auto insurance policies, splitted on 50% / 25% / 25% for train / validation / test sets,
- 56 features, which describe general information about a driver and its vehicle,
- 61% of drivers have no claims, 9% of drivers make 65% of all claims

Research Case II – TACT-HMC

Motivation

Bayesian learning with MCMC captures the uncertainty of the learned parameters. However, when the distribution of interest contains multiple modes, efficient exploration across all those modes becomes difficult. In particular, when the number of modes is large, the “distant” modes could be beyond the reach of any closest modes; this would lead to the so-called pseudo-convergence, where the ergodicity guarantee of MCMC methods breaks.

To make it worse, Bayesian learning on large datasets is typically conducted in an online setting: at each iteration, only a mini-batch of data are used to update the model. While the requirements for computation are substantially reduced, mini-batches introduce noise and hence additional uncertainty into parameters, which makes multimodal posterior sampling even more difficult.



Research Case II – TACT-HMC

Conventional attempt: Hamiltonian Monte Carlo

Hamiltonian Monte Carlo is the de facto standard for Bayesian sampling tasks. It first defines a Hamiltonian system upon the potential function of the form

$$U(\theta) = -\log \rho(\theta|\mathcal{D}) = -\log \rho(\theta) - \sum_{i=1}^N \log \ell(\theta; \mathbf{x}_i) - \text{const}$$

It then simulates the evolution of that system via the Hamiltonian dynamics

$$H(\Gamma) = U(\theta) + \mathbf{p}_\theta^\top \mathbf{M}_\theta^{-1} \mathbf{p}_\theta / 2$$

The Metropolis-Hastings test will be performed at last, serving as a correction for the discretization errors. In the full-batch setting, HMC ends up in a biased histogram, which fails to explore some of modes.



Research Case II – TACT-HMC

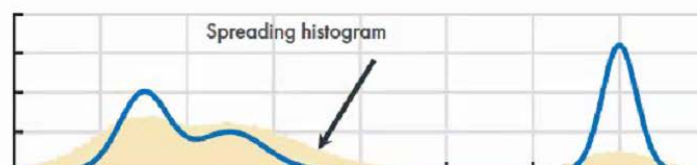
Ingredient I: Continuous Tempering

In physics, continuous tempering is currently a state-of-the-art method to accelerate the exploration of complex free energy surface by means of continuously and systematically varying the temperature of a physical system. It extends the original Hamiltonian system in a way that

$$H(\Gamma) = \lambda(\xi)U(\theta) + W(\xi) + \mathbf{p}_\theta^\top \mathbf{M}_\theta^{-1} \mathbf{p}_\theta / 2 + p_\xi^2 / 2m_\xi$$

By simulating the Hamiltonian dynamics, the extended system travels through the entire phase space.

However, when moving to the mini-batch setting, the noise by mini-batching perturbs the trajectory, leading to a spread histogram



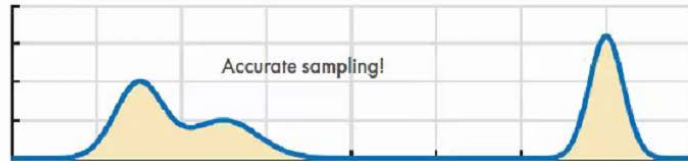
Research Case II – TACT-HMC

Algorithm

Algorithm 1 Thermostat-assisted continuously-tempering Hamiltonian Monte Carlo

Input: stepsize η_θ, η_ξ ; noise level c_θ, c_ξ ; (rescaled) thermal inertia $\gamma_\theta, \gamma_\xi$; unit interval of simulation K_0

- 1: $r_\theta \sim \mathcal{N}(0, \eta_\theta I)$ and $r_\xi \sim \mathcal{N}(0, \eta_\xi)$; $(z_\theta, z_\xi) \leftarrow (c_\theta, c_\xi)$
- 2: INITIALISE($\theta, \xi, \text{abf}, \text{samples}$)
- 3: **for** $k = 1, 2, 3, \dots$ **do**
- 4: $\lambda \leftarrow \text{LAMBDA}(\xi)$; $\delta\lambda \leftarrow \text{LAMBDA DERIVATIVE}(\xi)$
- 5: $z_\xi \leftarrow z_\xi + \delta\lambda^2 [r_\xi^2 - \eta_\xi] / \gamma_\xi$
- 6: $z_\theta \leftarrow z_\theta + \lambda^2 [r_\theta^T r_\theta / \dim(r_\theta) - \eta_\theta] / \gamma_\theta$
- 7: $\mathcal{S} \leftarrow \text{NEXTBATCH}(\mathcal{D}, k)$; $\delta A \leftarrow \text{abf}[\text{ABFINDEXING}(\xi)]$
- 8: $\tilde{U} \leftarrow \text{MODELFORWARD}(\theta, \mathcal{S})$; $\tilde{f} \leftarrow \text{MODELBACKWARD}(\theta, \mathcal{S})$
- 9: $r_\xi \leftarrow r_\xi - \delta\lambda [\eta_\xi \tilde{U} + \mathcal{N}(0, 2c_\xi \eta_\xi)] - \delta\lambda^2 z_\xi r_\xi + \eta_\xi \delta A$
- 10: $r_\theta \leftarrow r_\theta + \lambda [\eta_\theta \tilde{f} + \mathcal{N}(0, 2c_\theta \eta_\theta I)] - \lambda^2 z_\theta r_\theta$
- 11: ABFUPDATE($\text{abf}, \xi, \delta\lambda, \tilde{U}, k$)
- 12: $\xi \leftarrow \xi + r_\xi$
- 13: **if** ISINSIDEWELL(ξ) = **false** **then** ▷ ξ is restricted by the well of infinite height.
- 14: $r_\xi \leftarrow -r_\xi$; $\xi \leftarrow \xi + r_\xi$ ▷ ξ bounces back when hitting the wall.
- 15: $\theta \leftarrow \theta + r_\theta$
- 16: **if** $k = 0 \bmod K_0$ and $\lambda = 0$ **then**
- 17: APPEND($\text{samples}, \theta$) ▷ θ is collected as a new sample in samples .
- 18: $r_\theta \sim \mathcal{N}(0, \eta_\theta I)$ and $r_\xi \sim \mathcal{N}(0, \eta_\xi)$ ▷ r_θ, r_ξ is optionally resampled.
- 19: **function** ABFUPDATE($\text{abf}, \xi, \delta\lambda, \tilde{U}, k$)
- 20: $j \leftarrow \text{ABFINDEXING}(\xi)$ ▷ ξ is mapped to the index j of the associated bin.
- 21: $\text{abf}[j] \leftarrow [1 - 1/k] \text{abf}[j] + [1/k] \delta\lambda \cdot \tilde{U}$



Research Case II – TACT-HMC

Simulation: 2D mixture of Gaussian

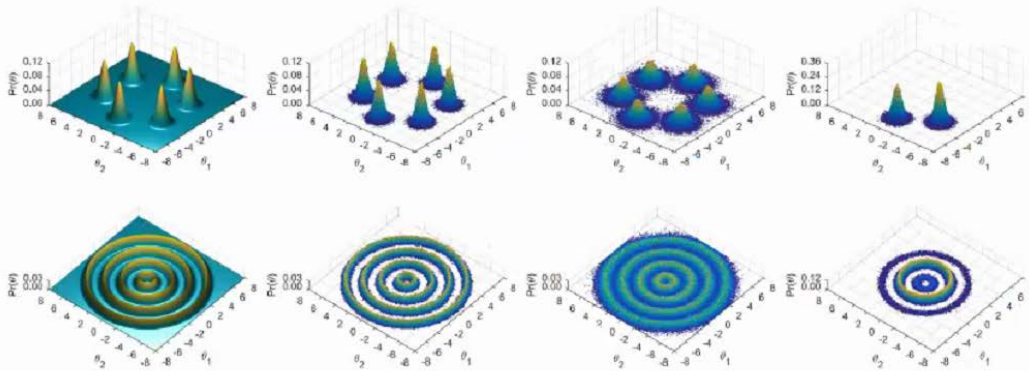


Figure 2: Experiments on sampling two 2d synthetic distributions. *Left:* The distributions to sample; *Mid-left:* Histogram of samples drawn by TACT-HMC; *Mid-right:* Histogram by the well-tempered sampler without thermostats; *Right:* Histogram by the thermostat-assisted sampler without tempering.

Deevlopment

Computer Vision: the field that designs algorithms and builds machines that can see

- The Advent of **Deep Learning** has disrupted **Large-Scale Visual Recognition and Understanding**
- Deep Learning in CV: brain-inspired Deep Neural Networks (DNNs) trained on millions of labeled images **achieve (super) human-level performance in object classification** (e.g., Microsoft's PReLU-net in 2015 ImageNet 1000-class object classification)
- Deep Learning goes beyond object detection/recognition by **unveiling context in the visual domain**
- **Convolutional Neural Networks (CNN)**: main building-blocks that act as **multi-scale (unsupervised) representation learners** → no need for domain knowledge & handcrafted features



Example Images from the ImageNet ILSVRC

- Transfer learning exploits structure among interrelated visual tasks: Reuse a pre-trained model on a new task
- Example : The tasks of object detection & segmentation are trained jointly → instance segmentation



"I think Transfer Learning is the key to General Intelligence",
Demis Hassabis, CEO, DeepMind



"Taskonomy: Disentangling Task Transfer Learning",
Zamir et al., (best paper award CVPR 2018): explicitly model the structure of the visual tasks space

The number of data points needed for solving a set of 10 tasks can be reduced by 2/3 while keeping the performance the same !!!

DEVELOPMENT

Computer Vision Use Case I: Commercial Property (CP) Underwriting & Investment

Landscape: **Property** --- a significant portion of UW and Investment books --- **faces multiple data issues**

Non-Life and Property Insurance

Underwriting



Motor
Property
General liability
Surety
Other

- European P&C premiums totalled **€363bn** in 2016
- Property Premiums amounted to **€99bn > 27% of the P&C total.**

Breakdown of Non-Life premiums in Europe 2016



Insurers' investment portfolio in 2016 was equivalent to 61.9% of the EU's GDP

Commercial Property: attractive thanks to (a) higher yields, (b) long-term capital growth, (c) Better portfolio diversification, (d) flexible invest options (e.g., peer-to-peer, crowdfunding, funds and investment trusts)

Investments

Data Acquisition & Quality Issues in the Insurance Sector

1. **Property Underwriting** based on **primary risk modifiers** (e.g., construction type) and **secondary risk modifiers** of lower importance
2. **Unreliable & Expensive Data** collected from unreliable public records or pricy in-person inspections
3. **Low data quality** (incomplete, duplicate, inaccurate, outdated) due to the way business is transacted and lack of data sources



Detrimental impact on response to market & portfolio analytics → risk selection issues, cost/inefficiency of capital & RI purchasing, unknown exposure

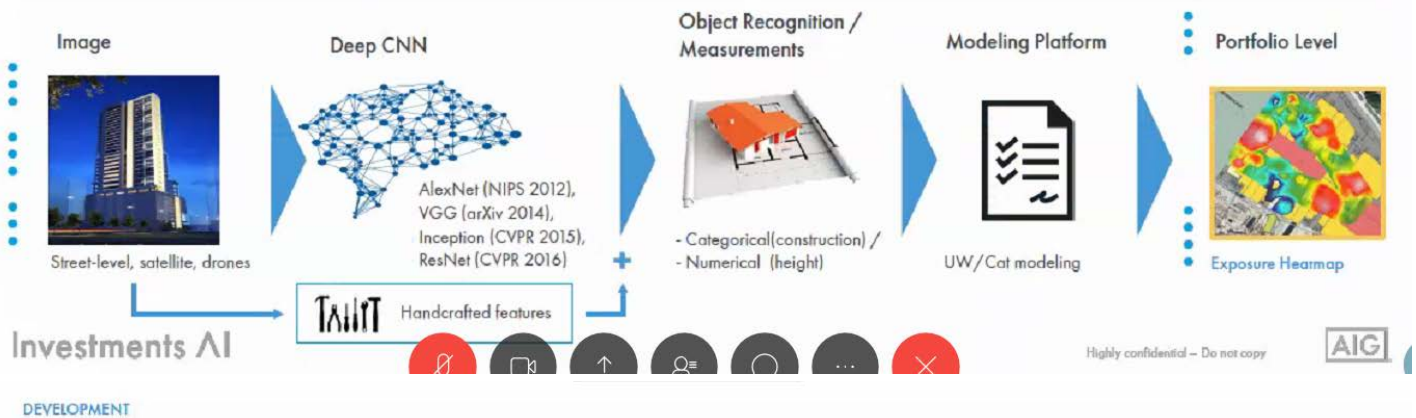


Computer Vision Use Case I: Commercial Property (CP) Underwriting & Investment

Vision: Apply Computer Vision & Machine Learning on image data to innovate data acquisition

Fully-automated Risk Modifiers Estimation

- Many risk modifiers can be identified from images
- Formulate automated modifier estimation as Supervised Learning $y = f(x)$:
Learn the mapping $f(\cdot)$ that assigns data point x (property image) \rightarrow modifier y (e.g., construction type)
- Deep Learning & Transfer Learning: Apply Deep CNNs pre-trained on large-scale vision datasets on property images

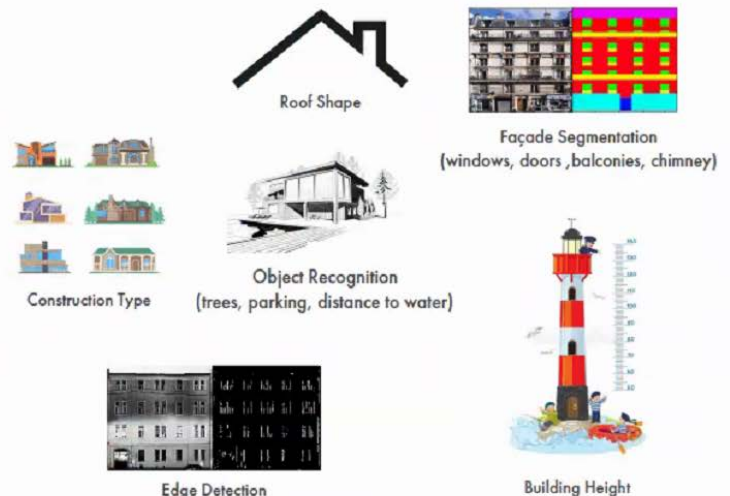
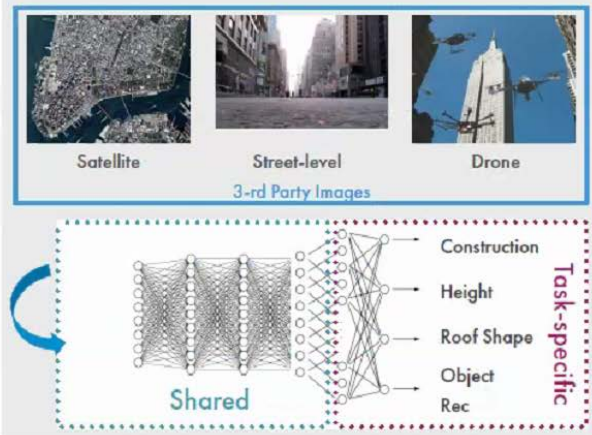


Computer Vision Use Case I: Commercial Property (CP) Underwriting & Investment

Methodology: Transfer and/or Multi-Task Learning with Deep Models to exploit low-level similarities shared across features

Assumption: Discriminative cues are shared across interrelated features.

- Shared Layers: coarse features (e.g., edges, texture)
- Task-Specific Layers: classification/regression / counting



Computer Vision Use Case II: Auto Damage Detection



Computer Vision Use Case II: Auto Damage Detection

CRITICAL PAINPOINTS FOR THE CLAIM INDUSTRY

High Processing Cost: costs due to *labour-intensive appraisal procedure* & *Elongated Claim Processing*: customer dissatisfaction → *costly turnover*

I. Significant Processing Cost*

- North America, 2016: 26M auto claims with \$22B total claim payout
- Three major processing costs account for 32% of the total claim payout (~\$7.0B):
 1. Car Rentals (\$3.7B): 40% of claims, Avg. 12 days at \$30/day
 2. Vehicle Storage (\$1.5B): 4.4M total loss claims spent an Avg. of \$344/claim in storage fees (Avg. 17 days)
 3. Adjusters (\$1.8B):
 - Repairable claims: 30% Independent Adjusters at 150/claim, 24% Insurers' Staffed Adjusters (11k employed in US at \$65,000/year), 4% Independent Photo Appraisers at \$150/claim
 - Frequent supplemental appraisal (>50%) costing \$125/claim

II. Elongated Claim Processing

- 5-15 days for Repairable Claims, 30 days for Total Loss Claims
- 88% of displeased claimants avoided the "definitely will renew" response and 93% avoided the "definitely will recommend" their current insurer (J.D. Power 2016 U.S. Auto Claims Satisfaction Study)
- 7x- 9x higher cost to attract a new customer than to retain one
- 2014: traditional auto insurance companies spent an avg. of \$792/policy on new customer acquisition

Computer Vision Use Case II: Auto Damage Detection

Automatic Car Damage Detection system

Summary

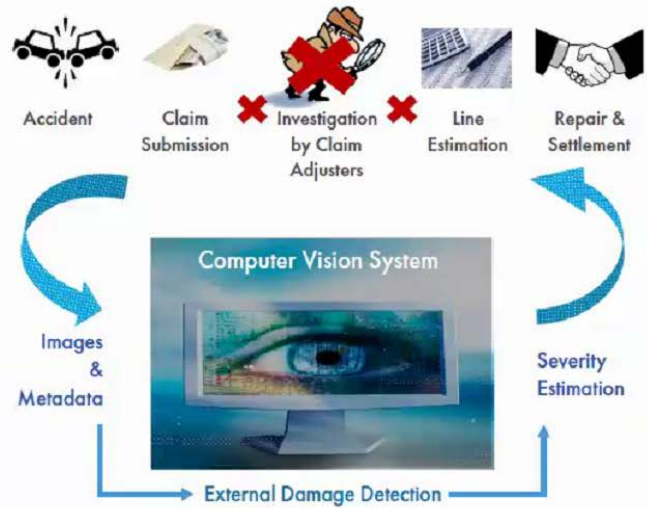
Automatic Car Damage Detection: end-to-end *Computer Vision* and *Machine Learning* solution that prepares an assessment of damages to a vehicle when provided with images of the exterior of the vehicle along with the vehicle's make, model and year.

Product

- Convolutional Neural Networks (CNN) *learn to assess exterior*
- Coupled with a database of parts and labour cost, the list of damaged parts thus predicted can be trained to *predict the parts and labour cost*.

Use Cases

- Automated Repair Cost Estimation & Total Loss Prediction
- Repair shop Early Notification
- Reduction in Storage Time:
- Improved Customer Satisfaction
- Reduction of Fraud



Investments AI * \$94M-\$188M assuming 5-10%

Highly confidential – Do not copy



Yuanyuan Liu, D.Phil. (Oxon)

Director, Statistical Machine Learning
Investments AI | Investment
+44-2076-516247
yuanyuan.liu@aig.com

Thanks