Institute and Faculty of Actuaries

More than Just a Big Idea: How big data and deep learning is helping Japanese insurers to protect homeowners from Nat Cat risk?

Takeshi Okazaki & Oriol Gaspa Rebull
Aon Benfield

12 May 2017

Institute and Faculty of Actuaries

Agenda

- Big Data Impact in Insurance
- Deep Learning
- Aon Benfield Motivation
- Application and Products
- Summary

12 May 2017

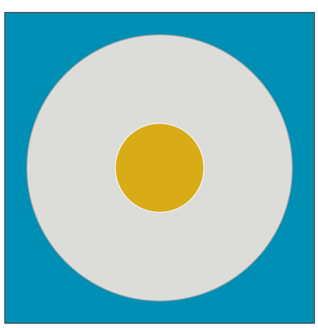
Data: The Raw Ingredient of Decision Making

data

Big Data

How Does More Data Impact Risk and Insurance?

- Incomplete understanding creates opportunities for insurance markets
- Ignorance and certain knowledge generally rule out insurance



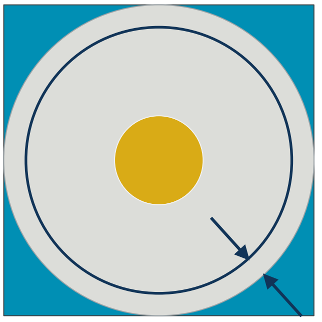
Unknown, ignorance, no insurance

Partial knowledge, uncertainty, risk, insurance

Complete knowledge, certainty, managed, retained

… What's The Impact of More Observations?

- **More observations can create markets**
- Risk measured by risk owners
- Measurement begets management
- Risk more quantifiable for insurers



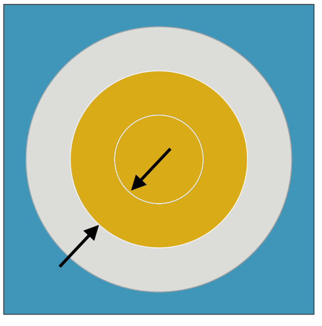
Insurance gain from decreased ignorance

More data is a good thing:

Emerging Risks

… What's The Impact of More Parameters?

- **More parameters may destroy markets in the long run**
- More granular underwriting
- Less risk sharing
- Affordability and availability issues



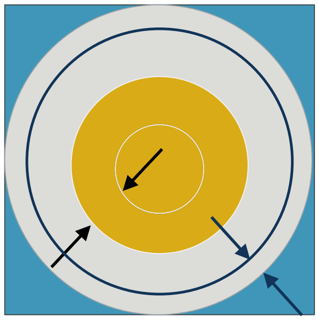
Insurance loss from greater certainty

More data is a bad thing:

Existing Risks

How Does More Data Impact Risk and Insurance?

- **Net growth impact on insurance risk indeterminate**



- **Different data models apply in different markets**

More data is :

Disruption

Institute and Faculty of Actuaries

Agenda

Big Data Impact in Insurance

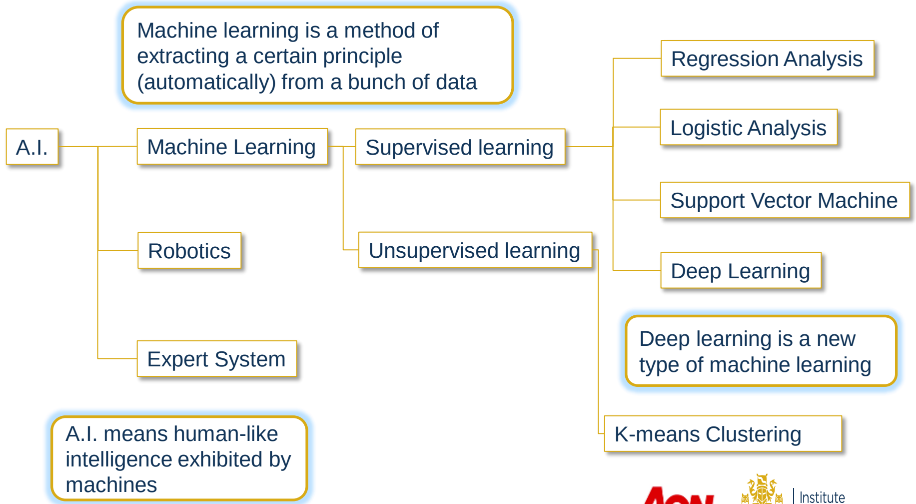
Deep Learning

Aon Benfield Motivation

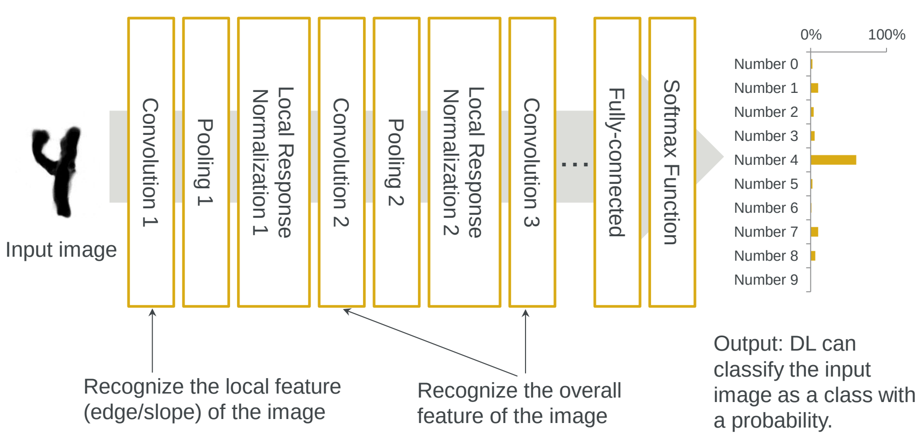
Application and Products

Summary

Machine Learning (ML) and Deep Learning (DL)

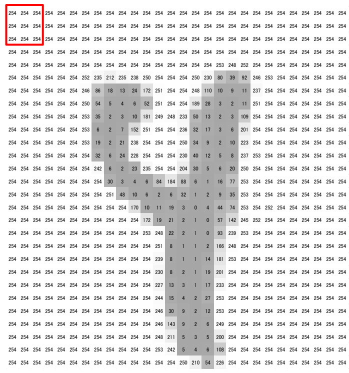


An Example of the Network of Deep Learning (DL)



Convolutional Layer

Input image

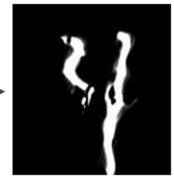


Digital image consists of pixels

The filter 1 highlights the vertical line

$$\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

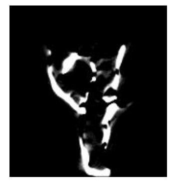
Filter 1



The filter 2 highlights the horizontal line

$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

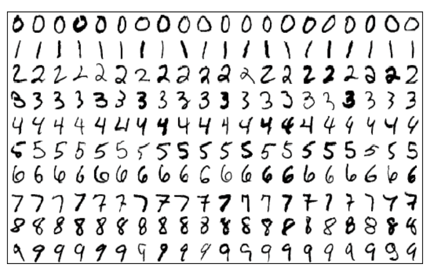
Filter 2



- A pixel in gray scale shows the value between 0 and 255.
- A convolutional layer is a process of extracting image-features by a filter.
- DL is able to learn the appropriate pattern of the filter automatically.

Deep Learning Test Case

- The MNIST database of handwritten digits has a training set of 60,000 examples, and a test set of 10,000 examples.
- The digits have been size-normalized and centered in a fixed-size image.



THE MNIST DATABASE of handwritten digits
http://yann.lecun.com/exdb/mnist/

SVM was a traditional best method before deep learning appeared.

Classifier	Accuracy rate
Support Vector Machine (SVM)	89%
Convolutional Neural Network (Deep Learning)	98%

Institute and Faculty of Actuaries

Agenda

- Big Data Impact in Insurance
- Deep Learning
- **Aon Benfield Motivation**
- Application and Products
- Summary

12 May 2017

Japan and Its Natural Catastrophes

1959 Vera typhoon

Source: Devastating Disasters

2004 Songa typhoon

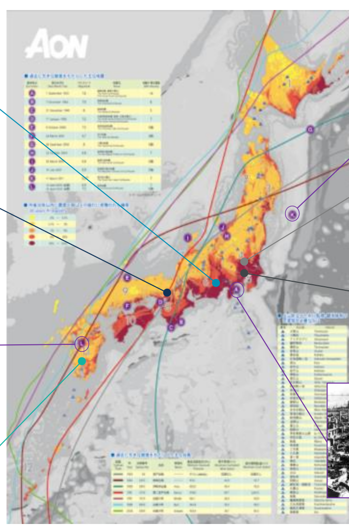
Source: The BBC

2016 Kumamoto earthquake

Source: AGU

2016 Sakurajima volcano

Source: The BBC



2011 Tohoku-Oki earthquake

Source: Encyclopaedia Britannica

2015 Joso Flooding

Source: Aon Benfield

2014 Severe winter weather

Source: Wikipedia

1923 Kanto earthquake

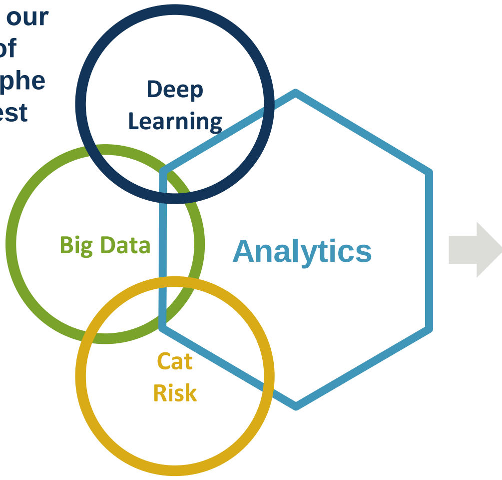
Source: The Atlantic

AON Empower Results®

Institute and Faculty of Actuaries

The Challenge …

… is to improve our understanding of natural catastrophe risk to the highest resolution possible



New products and ideas

Institute and Faculty of Actuaries

Agenda

- Big Data Impact in Insurance
- Deep Learning
- Aon Benfield Motivation
- **Application and Products**
  - **Methodology**
  - Typhoon Claims Estimation
  - Building-level Insurance Rating
- Summary

The Challenge with Typhoon Modelling

- It is well known that a building roof is very vulnerable to strong wind caused by a typhoon.
- If the information on roof shape/condition is obtained, it is possible to estimate a typhoon risk more accurately.
- However, as roof-related information is typically not collected during insurance contract making, the development of database has been a longstanding problem.

Source: The Asahi Shimbun Company

Reference:
Takeshi Okazaki, “Application of Typhoon Model in the Non-Life Insurance Industry”, Wind Engineers, JAWE, 2016, Vol. 41, No. 2, pp. 152-160
https://www.jstage.jst.go.jp/article/jawe/41/2/41_152/_article/-char/ja/

AON Empower Results®

Institute and Faculty of Actuaries

Roof Shape Classification in Japan

The roof shape in Japan can be mainly classified into the following five types.

gambrel roof	gable roof	hipped roof	square roof	flat roof
入母屋屋根	切妻屋根	寄棟屋根	方形屋根	陸屋根

Vulnerability to strong wind

\+ —

AON Empower Results®

Institute and Faculty of Actuaries

Classify Roof Shape: Learning Process of DL

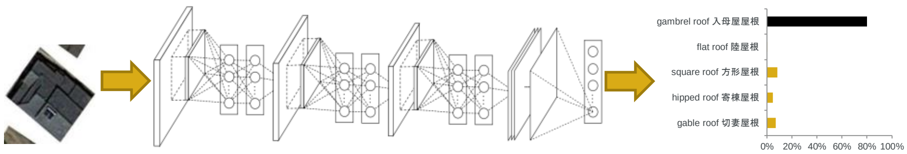
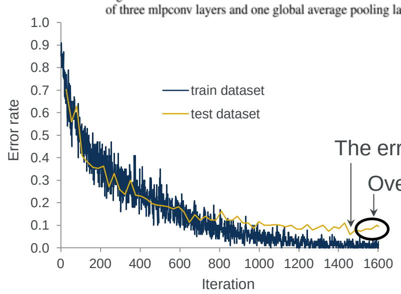


Figure 2: The overall structure of Network In Network. In this paper the NINs include the stacking of three mlpconv layers and one global average pooling layer.

Reference: "Network in Network", M Lin, Q Chen, S Yan, International Conference on Learning Representations



The error rate is 6% (The accuracy rate is 94%)

Classifier	Accuracy rate
Convolutional Neural Network (Deep Learning)	94-98%

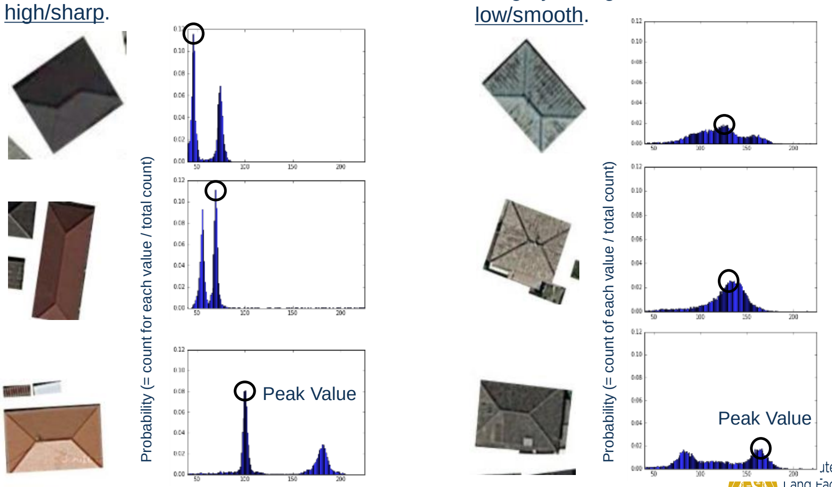
International patent application applied for in the US

Classify Roof Shape: Adjusting Input Image

Classify Roof Shape: Roof Condition

If a roof is not deteriorated, the peak value of the grey histogram tends to be high/sharp.

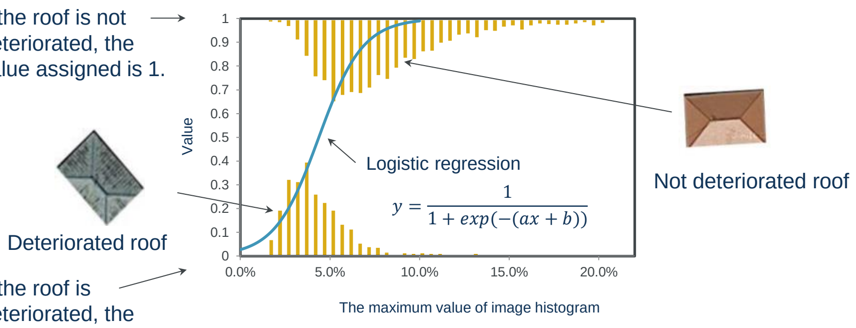
If a roof is deteriorated, the peak value of the grey histogram tends to be low/smooth.



Classify Roof Shape: Roof Condition (2)

If the roof is not deteriorated, the value assigned is 1.

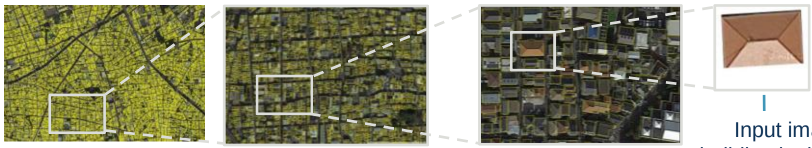
If the roof is deteriorated, the value assigned is 0.



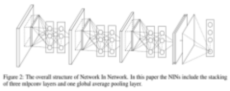
Classifier	Accuracy rate
The maximum value of image histogram in gray scale	80 - 85%

International patent application applied for in the US

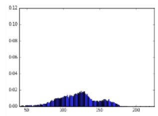
Summary Process of Roof Classification



Input image
building by building



Classify the roof shape using DL



Classify the roof condition by the maximum value of image histogram in grey scale

GPU processing

- Achieved a building coverage ratio of 100% for the whole Japan
- The building database also includes the building area and the coordinates.

65 million unique buildings

AON Empower Results®

Institute and Faculty of Actuaries

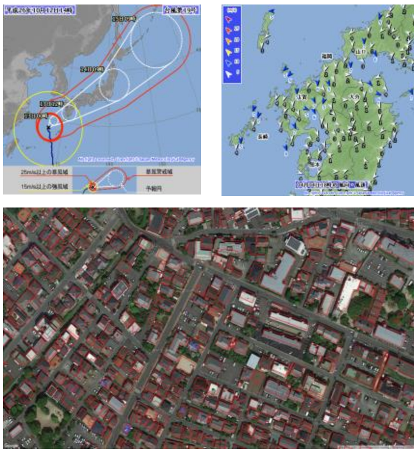
Institute and Faculty of Actuaries

Agenda

- Big Data Impact in Insurance
- Deep Learning
- Aon Benfield Motivation
- Application and Products
  - Methodology
  - Typhoon Claims Estimation
  - Building-level Insurance Rating
- Summary

Typhoon Claim Loss Estimation

- After a typhoon passes through Japan, observed wind speed from JMA are available (1300 stations country wide). With this data we can estimate the number of claims by combining the building database with the wind speeds.



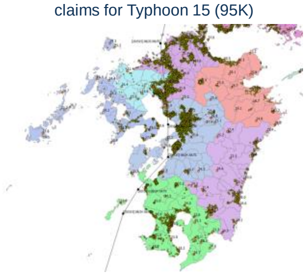
Using the building database, we can evaluate the prospective damaged buildings individually.

Vulnerability functions

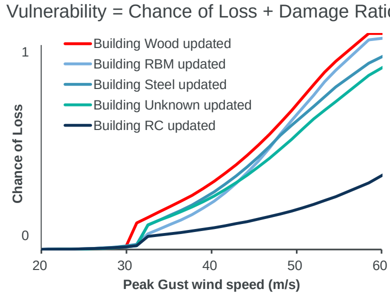
Estimation Results
- Total number of claims
- Location of damaged buildings

Updating of Damage Curves

Individual buildings reported claims for Typhoon 15 (95K)



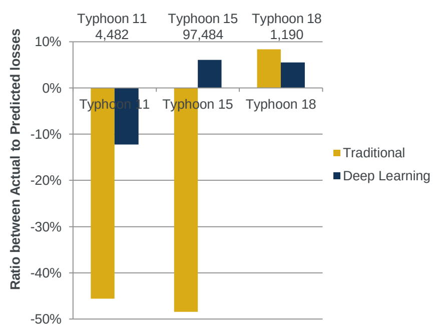
Vulnerability = Chance of Loss + Damage Ratio



- The existing available damage curves were created based on aggregated data (postcode) from 1998 to 2006
- With the DL technique we can study individual buildings and their roof damage to create more accurate vulnerability models based on their Chance of Loss (CoL)
- CoL is the probability of a property being affected by a typhoon or not. Chance of loss is an integral part of damage curves

Results

- Results using the typhoon damage prediction system were compared to actual payments (as of July 2015).
- Benchmarking was performed for three different typhoons in 2015 and we are now working on 2016 data
- The improvement on damage prediction is substantial for medium to large storms



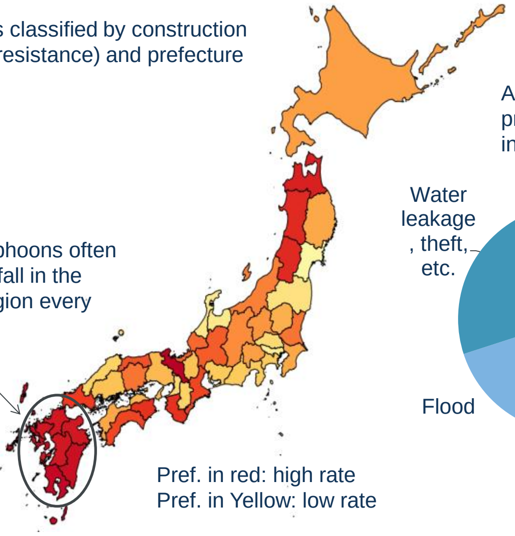
Agenda

- Big Data Impact in Insurance
- Deep Learning
- Aon Benfield Motivation
- Application and Products
  - Methodology
  - Typhoon Claims Estimation
  - Building-level Insurance Rating
- Summary

Japan's Standard Fire Insurance

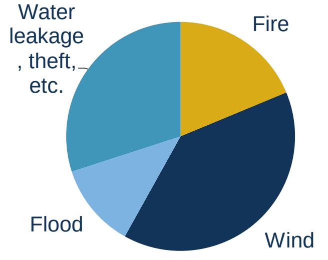
The tariff is classified by construction class (fire resistance) and prefecture

Several typhoons often make landfall in the Kyusyu region every year

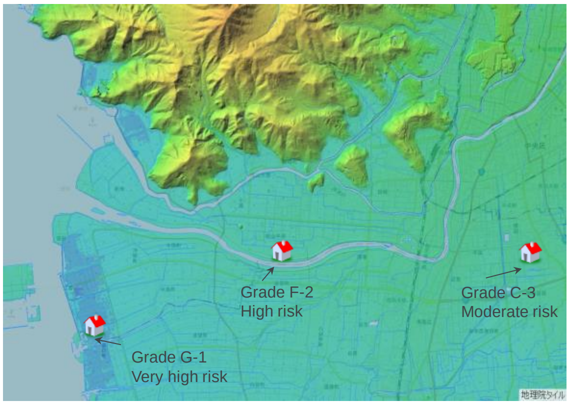


Pref. in red: high rate
Pref. in Yellow: low rate

A breakdown of pure premiums for residential insurance



The Concept of Building-level Insurance Rate

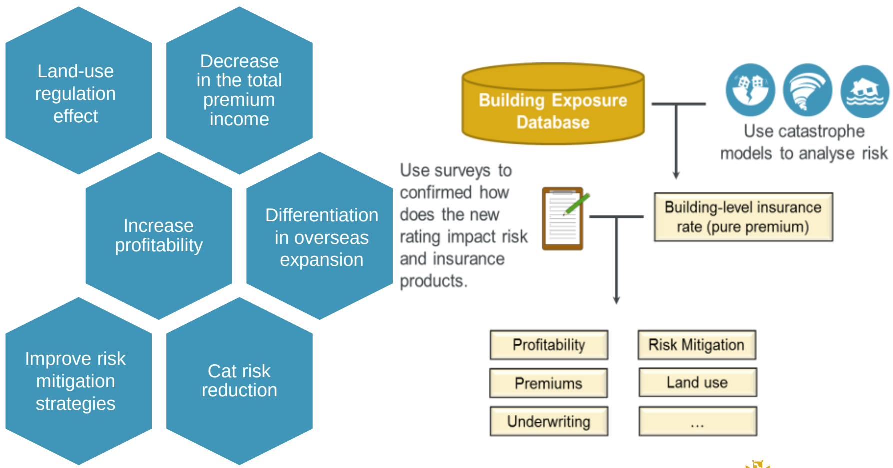


Grade A-1
Grade A-2
Grade A-3
Grade A-4
Grade A-5
Grade B-1
Grade B-2
. . .
. . .
. . .
Grade F-4
Grade F-5
Grade G-1
Grade G-2
Grade G-3
Grade G-4
Grade G-5

High rate

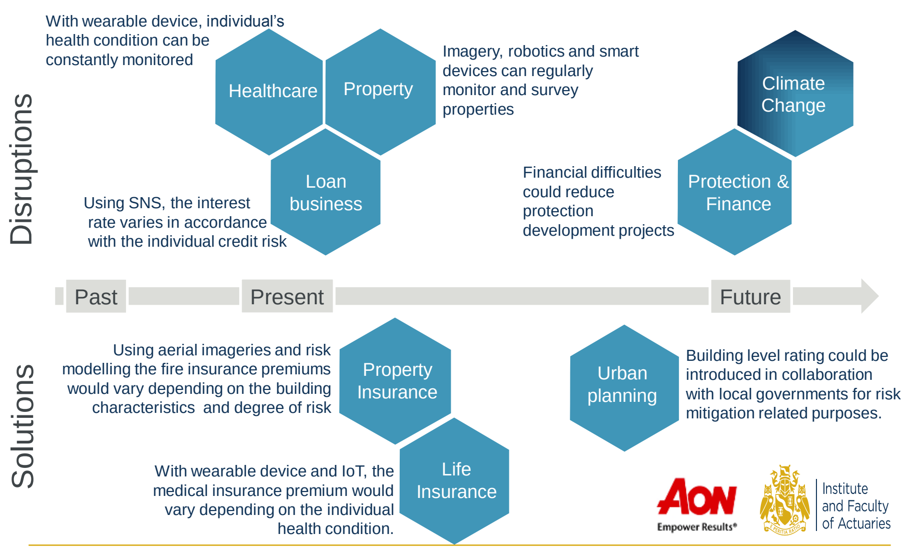
- Each building can be classified by a combination of:
  1. Construction characteristics (materials, height, roof type, year built …)
  2. Geophysical characteristics (location, elevation, gradient …)
  3. Risk characteristics (flood, earthquake, storm surge …)

Potential Impact of Building-level Insurance Rate



What Could Fire Insurance Cover in the Future?

The function of fire insurance is to financially safeguard victims from damaging events but could this change in the future as more disruption arises?



Institute
and Faculty
of Actuaries

Agenda

- Big Data Impact in Insurance
- Deep Learning
- Aon Benfield Motivation
- Application and Products
- **Summary**

24 May 2017

Summary

BIG Data

The combination of Big Data and Machine learning (DL) is one of the key innovation areas across the insurance sector

Deep Learning

Aon Benfield has used deep learning to identify roof characteristics across Japan and developed a building level exposure database including 65 million properties.

Innovation

The database can support the development of multiple insurance and non-insurance products

Risk

We believe disaster risks would be reduced by introducing a similar concept to the building-level rating in collaboration with local governments.

AON Empower Results®

Institute
and Faculty
of Actuaries

Questions

Special thanks to **Takeshi Okazaki** who has been developing Aon Benfield's Deep Learning Database

The views expressed in this presentation are those of invited contributors and not necessarily those of the IFoA. The IFoA do not endorse any of the views stated, nor any claims or representations made in this [publication/presentation] and accept no responsibility or liability to any person for loss or damage suffered as a consequence of their placing reliance upon any view, claim or representation made in this presentation.

The information and expressions of opinion contained in this publication are not intended to be a comprehensive study, nor to provide actuarial advice or advice of any nature and should not be treated as a substitute for specific advice concerning individual situations. On no account may any part of this presentation be reproduced without the written permission of Aon Benfield.

AON Empower Results®

Institute and Faculty of Actuaries