Society of Actuaries in Ireland

Reserving in the Pressure Cooker

(General Insurance TORP Working Party)

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Disclaimer

The views expressed in this presentation are those of the presenter(s) and not necessarily of the Society of Actuaries in Ireland

Work undertaken by members of the Towards Optimal Reserving Process (TORP) working party

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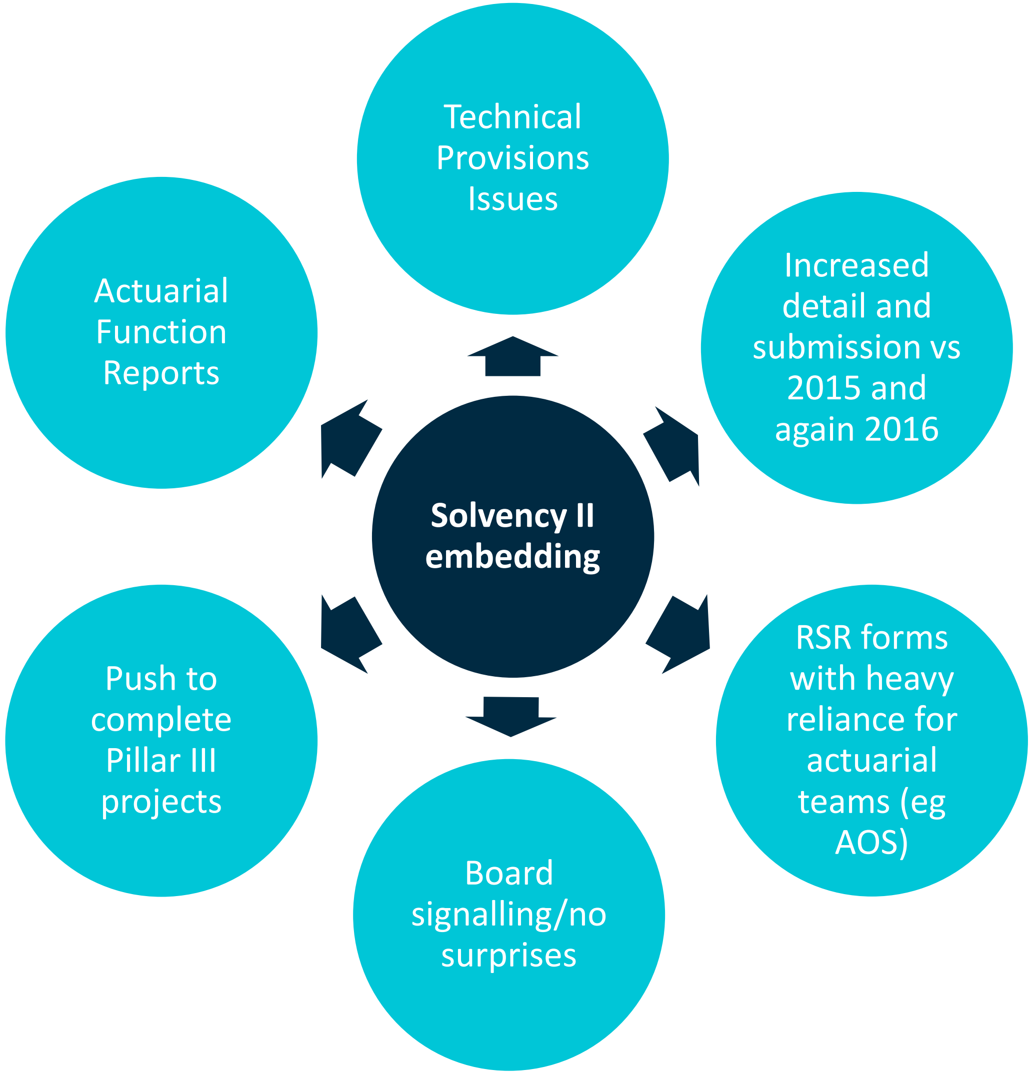
Reserving in the Pressure Cooker

- Solvency II embedding
- Timescales and pressures on the Reserving Actuary
- No surprises reserving
- Automation survey
- Machine Learning
- Questions

Solvency 2 Embedding



Solvency II embedding (2)

Solvency II vs Bermuda vs Swiss

Discounted Reserves vs Undiscounted Reserves

1 year view of reserve variability vs Ultimate view of reserve variability

Timescales and pressures

Timing and budget

- Reporting deadlines getting tighter
- Processes need to be faster and earlier
- Additional reporting; SII ~ GAAP ~ IFRS
- Soft market leads to added scrutiny
- Management demand ‘no surprises’
- Expenses and budgets under pressure
- Increased understanding of new requirements with time but what next?

Quality

- Do tighter timescales lead to reduced quality?
- Capital models push diversification; more classes needs more time
- Perfect storm – tight deadlines and new / increased regulation
- Do you provide insight and add value?
- Streamlining? Automation? AI?

Optimal processes should be both efficient and add value

No Surprises reserving

No surprises for whom?

- Board or lower level committees (e.g. Reserving / UW committee)?
- What is the materiality level of a ‘surprise’?
- Pre agreed actions?

No Surprises reserving

No surprises for whom?

Managing stakeholders through the process

- AvE
- Discuss trends
- Highlight potential changes (e.g. legislation) and impact
- Presentation to Reserve Committee in advance of booking numbers
- Analyse and explain uncertainty

No Surprises reserving

No surprises for whom?

Managing stakeholders through the process

Closer Relationships

- Included in discussions to minimise surprises
- Pricing / Reserving / Capital / Planning feedback loops
- Understand the business and how mix is changing
- Scenario test potential events and impact / reaction if they occur
- Watchlists for potential claims (and probability)

Automation Survey

Your reserving process – and embedded automation

Opportunity or threat

Reinsurance netting down

Reporting automation including Solvency II

IFRS automation based on work to date

Automation vs offshoring

Automation Survey

Data quality often poor and requires processing

IFRS seen as an impetus for automation

Currently considerable amount of manual work in the reserving process

Opportunity for automation in report generation

Machine learning an option when enough data but skills and costs a barrier

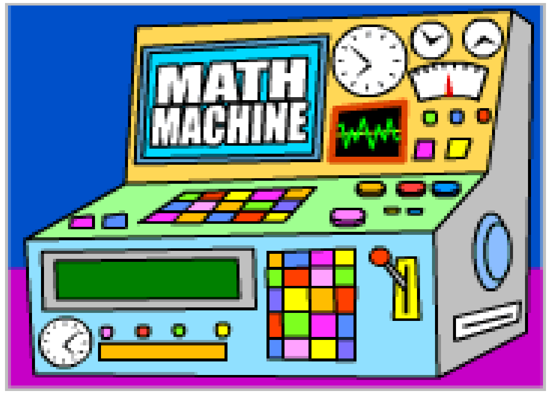
Opportunity to minimise errors, work faster and allow more time for analysis

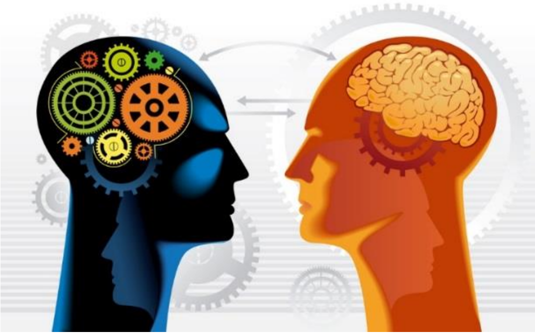
Automation Survey Summary Results

- No. of participants: **39**, among which:
  - **50%** are personal lines insurers;
  - **40%** are Lloyd's/London Market;
  - **10%** reinsurers or health insurers.
- Mix of small, medium and large measured by Gross SII TP volumes:
  - **25%** less than £100m;
  - **20%** between £100m and £500m;
  - **20%** between £500m and £1bn;
  - **35%** more than £1bn.

- Survey participants currently use:
  - Off-the-shelf software -> ~**50%**;
  - Excel s/s (exclusively) -> ~**25%**;
  - Internally coded platform ~**25%;**
- ~½ of largest firms use spreadsheets
- Automation qu responses:
  - **20%** as being mostly automated
  - **50%** -50/50 blend of manual+auto
  - **30%** as mostly or 100% manual
- ~**1/3** using off-the-shelf software described process as "**mostly manual**". However, for s/s users, only **1/4** have considered their process to be "mostly manual". Shows current software doesn't appear to have much impact on eliminating manual processes.

Machine Learning overview





- Popularity of machine learning driving innovation
- Can Machine Learning be used for reserving?
- Reduce information loss and improve insight
- Uptake limited by trade off of simplicity vs accuracy
- Companies now investigating different predictive techniques to mitigate the Mean Absolute Error (MAE)
- Machine learning 'blackbox' like but different machine learning methods which we can use:

  1. GBM (Gradient Boosting Machine)
  2. Decision Tree (the random forest)
  3. LASSO (least absolute shrinkage and selection operator)

The errors in the reserving estimates (over or under reserving) can be reduced by using machine learning; but more importantly…

One emerging view is that the errors in the reserving estimates can be explained much better by using machine learning on granular claims data.

The classical reserving methods use a one-size-fits-all approach, so it is difficult to learn from the actual vs expected. Machine learning could give insight here

Example:
If you use a single cumulative development factor for all bodily injury claims for the year 2016, the A vs E would not tell you which cohorts of injuries developed worse than expected.

Machine learning models use the claims and exposure features which affect the development, frequency and severity.

Simply put, machine learning would use algorithms to estimate a different development factor for brain injury vs muscle injury.

Parameter estimation involves learning from historical granular data, minimising the errors and back-testing the parameters.

It therefore allows for a more in-depth analysis of the actual vs expected, e.g. brain injuries may have deteriorated worse than expected

Although machine learning models are computationally intensive and complex, they can be implemented very easily once built.

Importantly, they can be rerun frequently within small intervals (say monthly) to monitor the actual vs expected.

One suggestion from the working party is not for machine learning to replace the traditional reserving techniques, but rather to **validate and enhance them.**

Importantly, in this case machine learning models should be used to understand and explain the actual vs expected, and over time, help to develop more granular assumptions for traditional models such as loss ratios, development factors, frequency and severity.

Summary Statistics

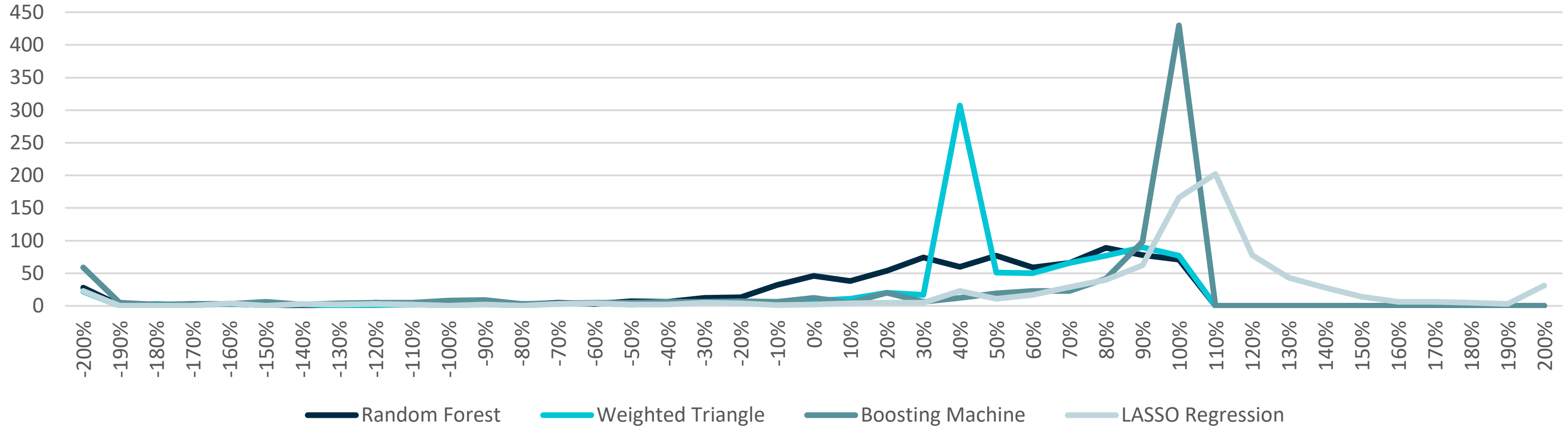
Method	Total Predicted	Actual	Actual vs Predicted	Mean Error %	Median Error %	Total Absolute Error	Absolute Error %
Triangle	16,764,770	15,685,367	1,079,403	7%	37%	12,474,066	80%
Forest	15,884,229	15,685,367	198,862	1%	43%	12,714,048	81%
GBM	15,639,526	15,685,367	(45,841)	0%	90%	20,462,309	130%
Lasso	25,064,981	15,685,367	9,379,614	60%	100%	32,916,272	210%

Comments

- Triangle = has lowest Absolute error but suffers higher mean error
- Forest = has slightly higher absolute error but very low mean error
- GBM = has lowest mean error but very high absolute errors, see predictions which are very sticky around mean mark
- Lasso regression = performs worst due to linear effect of the model, cannot capture the non-linear trends in the data

Machine Learning overview

Comparison of methods

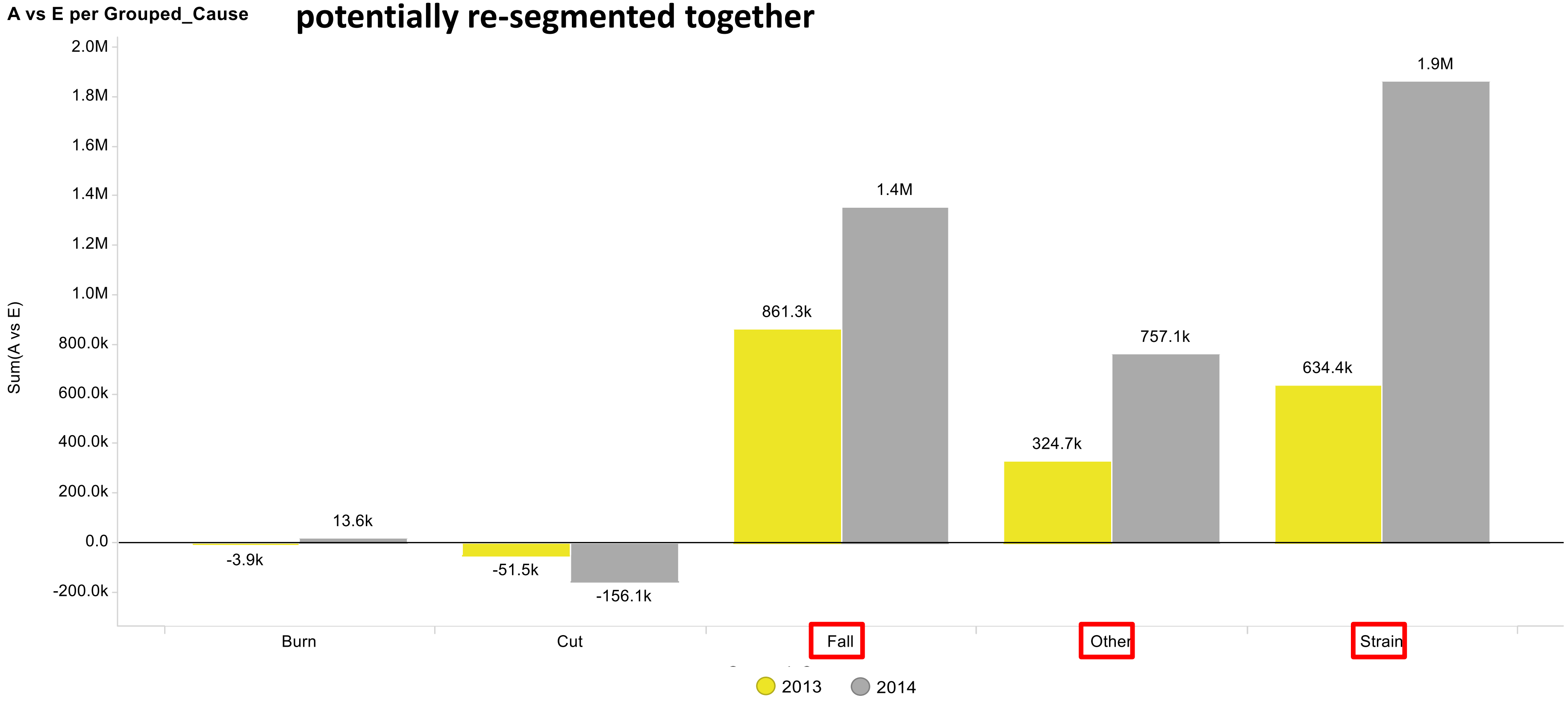


Commentary

- Employer's Liability Bodily Injury
- Large losses are not capped, large loss is >100K
- Prediction Error is (Actual - Expected)/Expected
- Total Claims 4815, split into 3972 Training 843 Tested (for prediction error check performance)
- Variables used - Incurred, Paid, Case, Type of Injury, Part of Body, State

Granular A vs E – Bodily Injury – Total (losses)

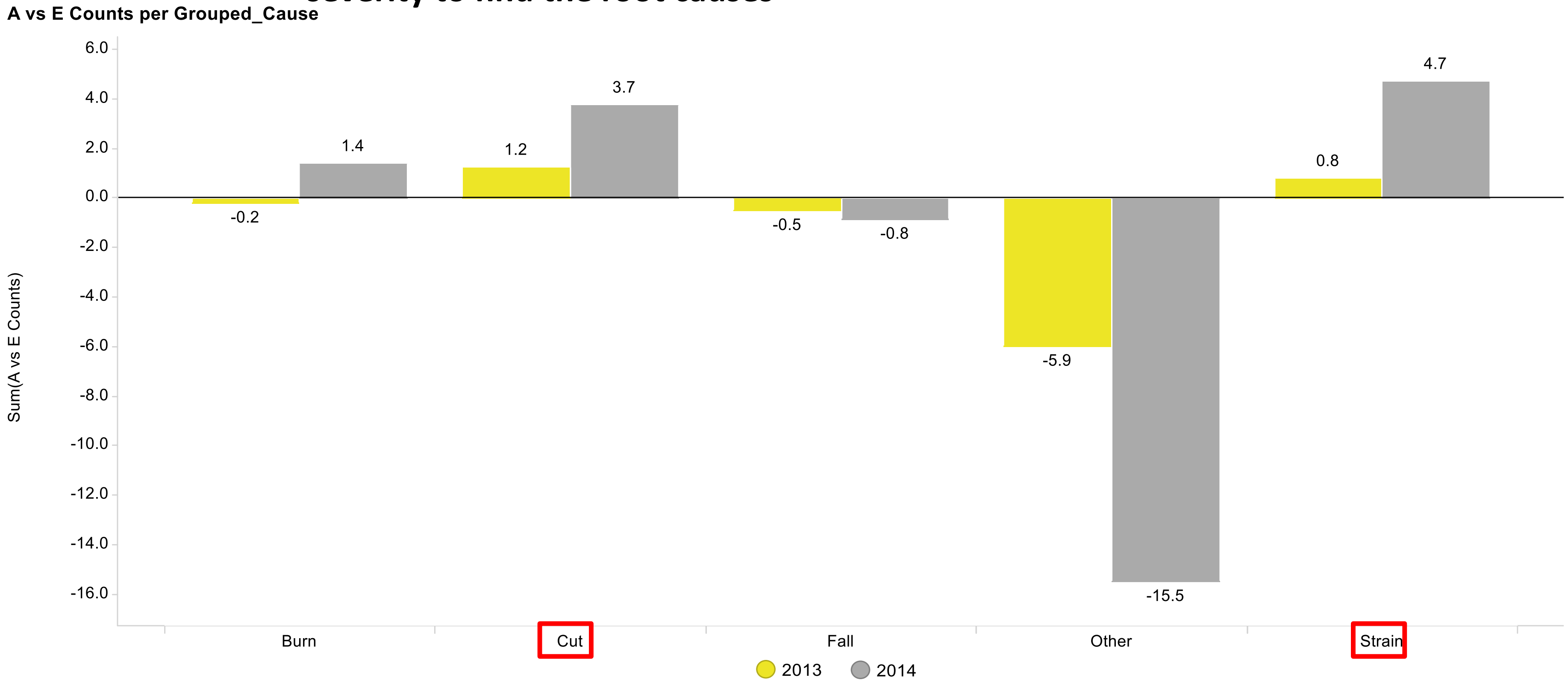
Claim types/injuries that consistently show adverse development can be potentially re-segmented together



<u>Advantages</u> – Easy insights into drivers of adverse development, also feeds back valuable information from reserving to business planning and analytics

Granular A vs E – Bodily Injury – Counts

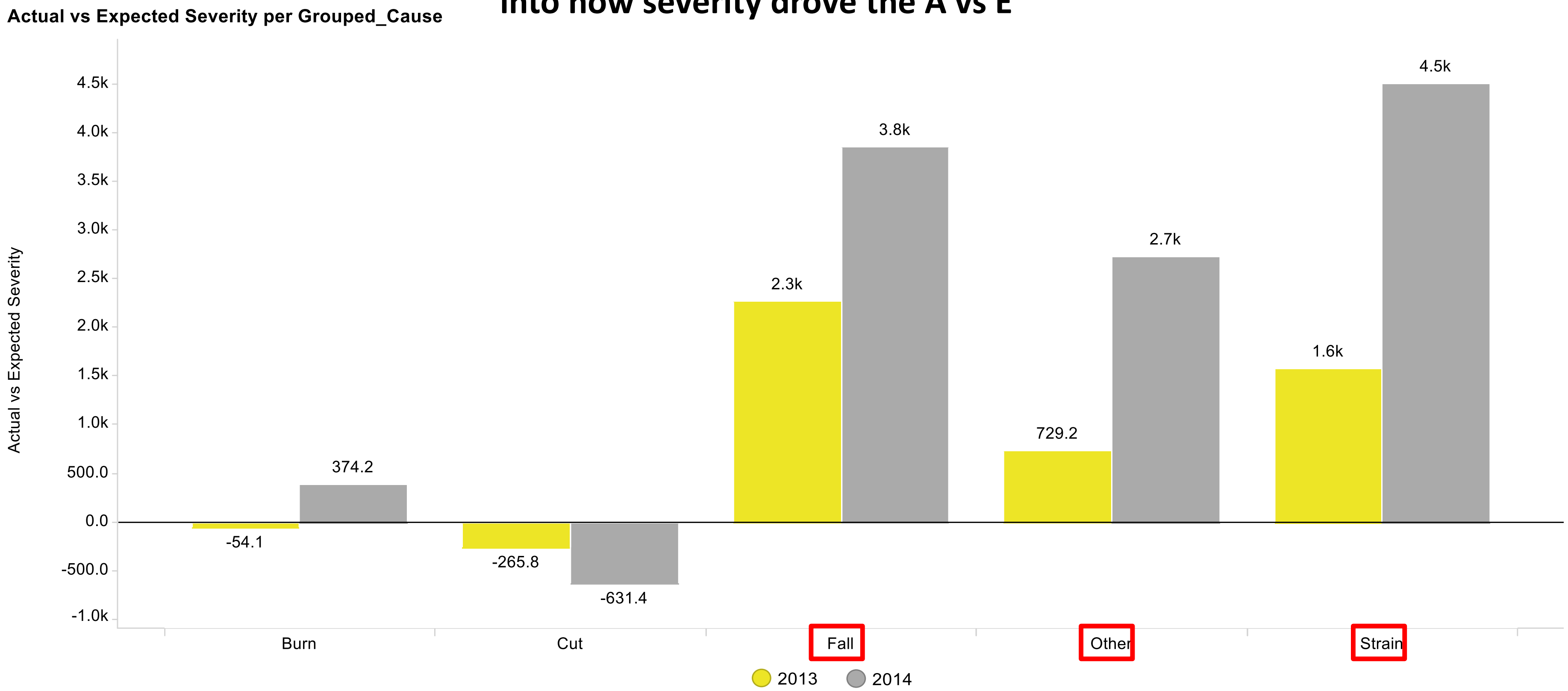
This adverse development can be further broken down into frequency and severity to find the root causes



For example, here we find counts A vs E is not significant, so it is actually severity that is driving the A vs E. So we can examine the severity data closely

Granular A vs E – Bodily Injury – Severity

Looking into the Actual versus Expected severity gives us more insights into how severity drove the A vs E



This can feed back *valuable* information into the reserving process, business planning as well as pricing analytics

Questions?