Using Predictive Modeling For Workers Compensation Ratemaking

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"I'M A LITTLE SURPRISED, WITH SUCH EXTENSIVE EXPERIENCE IN PREDICTIVE ANALYSIS, YOU SHOULD'VE KNOWN WE WOULDN'T HIRE YOU."

What Agents Hear When you Say
'We Are Introducing a Predictive Model into WC Ratemaking'

What we say to agents:

Last year, we introduced a predictive model that calculated the recommended schedule rating factor by policy. We reviewed how often you were deviating from the recommended schedule rating factor, and in 80% of the cases, you selected a schedule rating discount, when we were recommending a surcharge. Rather than a recommended schedule rating factor, we are introducing a new tiering factor that is based on a predictive model, and not subject to agent discretion.

What agents hear:

We caught you not using our predictive model based schedule rating recommendations and applying discounts to just get the sale, and have now increased all rates so you won't be able to sell anything.

WC Ratemaking Predictive Modeling History

- Some WC companies introduced predictive modeling several years ago, generally in underwriting and/or discretionary schedule rating.
- Helped companies differentiate risk better.
- Schedule rating is discretionary so some agents/underwriters deviated from proposed schedule rating so not perfectly implemented but step in right direction.
- Many WC companies have shifted to using predictive modeling via a non-discretionary class plan rating factor.
- Companies that have not done either are being selected against.

Selected Against Warning Signs

- Premium volume increasing or decreasing dramatically in a particular profile/segment of the market. For example, distribution of book changing geographically, by class, or by another policy or class profile.

- Generally, premium volume decreasing on profitable business and increasing on non-profitable business.

- If the Company has not yet performed a predictive model identifying profitable/ unprofitable segments, then it is possible the Company doesn't know the profitability of the various segments of their book.

- Overall loss ratio across entire book increasing.

Steps to Avoid Being Selected Against Using Predictive Modeling

1. Segment the book by future expected loss ratio to understand what your most to least profitable segments are.

   - Doing univariately ignores correlation between attribute and is sub-optimal.
   - Multi-variate predictive model better.
   - Identify the segment definitions, as well as segment distribution and other statistics, over time.

Steps to Avoid Being Selected Against Using Predictive Modeling

2. Use segment findings to:
   - Align agent compensation to sell most profitable business.
   - Realign rates via existing rating factor changes.
   - Introduce new predictive tiering model (All 3 best)

3. Introduce new predictive tiering model via schedule rating easy IT implementation & less regulatory review but allows agent / underwriting intentional manipulation and unintentional skewing.

4. Introduce new predictive tiering model via new class factor requires IT changes & subject to regulatory rate review but guaranteed to be used in rating.

Predictive Model Goal

- Identify profiles of best and worst loss ratio segments of book.
- Improve ability to target market most profitable segments and reduce marketing spend on least profitable segments.
- Improve ability to set the rate commensurate with risk.
- Improve risk differentiation at a more granular level.
- Combat being selected against.
- Select against competitors not using predictive modeling as best they can.

Steps to Create Predictive Model

1. Data prep at class level and policy level.
2. For each attribute with a significant shift in distribution across buckets over time (correlated with time) determine what is driving the shift.
3. Split prepped data between training and testing hold out.
4. Create model at policy level, if applying tier factors at policy level. Better than class level since considers interaction between classes.
5. Validate results with lift charts and other statistics.
6. Review results with business stakeholders. Important to investigate every instance of disbelief and get buy-in before proceeding.
7. Determine how to apply new tiers.
8. Roll-out plan, including communication to address resistance.

1. Data prep at class level and policy level

- On-level premium, especially class rates. Document data adjustments (ie: on-leveling) and non-adjustments (no loss development, incl. ALAE etc.)
- Match claims to policy attributes, at class level. Do not drop material number of umatched losses. Create an unkown class with $1 class premium to match to.
- Summarize data (earned exposure, actual premium, on level premium, reported claim counts, reported loss & ALAE, by policy year).
- Reconcile data summary to an outside source.
- For each attribute that you are going to test for predictive power in model, calculate distribution of buckets.
- Share data summary and distributions with stakeholders and get sign-off.

Data Prep Examples

- Collect earned exposure & premium on policies for selected time period (2006-2015).
- On-level premium to current rates by rerating every policy using current rates, factors, and rules. Determine whether to exclude or include schedule rating. Could rerate without schedule rating and then incorporate schedule rating as a derived variable.
- Reported claim counts and reported loss & ALAE associated with above policies at a particular valuation date. Determine if capping losses and if so at what limit.
- Premium untrended.
- Loss & ALAE undeveloped and untrended.
- Do NOT borrow from the future.

To Develop or Not to Develop, That is The Question Page 1

Intuitively appealing but LDF’s and trend limited for policy level relational analysis.

- LDFs include IBNER

- LDFs developed using triangle methodology appropriate for application to large sums of similarly partitioned data. Applying LDFs to individual claims or policies without attention to claim status (open or closed), size of claim (large or small), type of claim (indemnity or medical), and other unique claim and policy attributes is inappropriate.

To Develop or Not to Develop, That is The Question Page 2

- May need to include data summary with and without loss development to tie to an outside source or be understood by stakeholders.
- Segment to identify relative loss ratio or target variable; level is not the focus.
- Goal is to identify the relative difference of loss ratio (or alternative metric) between different attributes or different buckets within an attribute.
- If all segments develop & trend similarly then all “heights” would change equally proportionally. Relative segment positions unchanged.
- Perform correlation and distribution analysis to ensure no attribute correlated with time, so developing losses would not impact relative loss ratio level among buckets or attributes.

Data Prep – Data Summary by Year

Policy Year	Loss Ratio	Exposure (Payroll)	Earned Premium	Reported Loss & ALAE	Claim Count	Avg Premium Per $100 Payroll	Frequency Per Payroll	Severity	Pure Prem. Per $100 Payroll
2008									
2009									
2010									
2011									
2012									
2013									
2014									
2015									
TOTAL									

May need to also summarize by calendar year, develop losses, or other adjustments, to present to stakeholders in fashion they understand.

Univariate Statistics by Attribute

Sample Attributes	Signal	Noise	SNR	Buckets
Mill_Class_Base_Rate	4.96	0.03	142.91	-1 0 519 1192 1366 1518 1905 2370
PayrollClass	5.02	0.04	130.04	0 5 2150 5020 5484 6504 8041 8810 9010
Mill_payroll_class_factor	4.95	0.04	128.53	-1 0 7930841 17314964 35258248 67772192 113670224 293652224 588171840
Mill_EmployeeCt	3.81	0.03	120.40	-1 0 1 5 13 61
Mill_PerCapitaUnit	5.00	0.04	117.34	-1 0 62432 144395 296515 474446 876183 1931462 3754330
Mill_Claims_Free_ind	1.51	0.01	114.23	GT25K N Y
Mill_rpt_ind_loss_ALAE_3Yrs	1.51	0.01	111.40	GT25K N Y
EstimatedPayroll	3.29	0.03	97.47	0 50000 100000 200000 500000 1000000 5000000
Mill_Exposure	3.81	0.04	95.93	-1 0 62432 144395 296515 474446 876183 1931462 3754330
Mill_rpt_ind_loss_ALAE_2Yrs	1.32	0.01	95.21	GT25K N Y
Mill_1_1_11_Rate	3.68	0.04	92.11	-1 0 125 500 1000 1500
Mill_ClassDescription	3.93	0.12	32.06	Every Class Description
Mill_OLEAP	1.67	0.06	29.74	0 500 750 1000 2500 5000 7500 10000 15000 25000 30000 35000 4000 0 45000 50000 75000 100000 150000 250000
Mill_NewRenew	0.49	0.02	25.63	NEW BUSINESS RENEWAL Unknown
Mill_modified_Pure_premium	1.19	0.05	22.23	0 500 750 1000 2500 5000 7500 10000 15000 25000 30000 35000 4000 0 45000 50000 75000 100000 150000 250000
Mill_payroll_by_industry_group	0.85	0.04	20.91	-1 0 106306 249819 489454 870730 1454840 2465406 4969200
Mill_OLStdPrem	1.14	0.05	20.77	0 500 750 1000 2500 5000 7500 10000 15000 25000 30000 35000 4000 0 45000 50000 75000 100000 150000 250000
Mill_OLBasePrem	1.14	0.06	19.90	0 500 750 1000 2500 5000 7500 10000 15000 25000 30000 35000 4000 0 45000 50000 75000 100000 150000 250000
Mill_OLEAP_with_SR	0.55	0.03	16.33	0 407951 1403745 2433589 4453382 9368904 18067760
Mill_Avg_payroll_per_Emp_per_class	0.52	0.03	15.34	-1 0 2126812 2778016 3705250 5006389 6576266
Mill_Avg_OL_Prem_per_Emp_per_class	0.43	0.03	13.72	-1 0 1519718 3160662 4140345 5976350 9876650
Mill_Avg_payroll_per_Emp_per_policy	0.50	0.04	12.54	-1 0 2795575 4135250 6757088 10403250 18728200 41021500 141412848
Mill_Pol_Schd_Rtg_fct_vs_xMod_fct	0.30	0.03	10.39	-1 0 67568 82645 90917 100000 101020 111111 120482 131579
Mill_Current_Class_Rate	0.25	0.03	8.22	0 932 1166 1456 1764 2229
Mill_Industry_group	0.18	0.03	6.78	1 10 11 13 14 OTHER

2. For each attribute with a significant shift in distribution across buckets over time (correlated with time) determine what is driving the shift.

- For long tail lines, this could make the loss ratio for the attribute bucket where distribution has shifted to look better because it is less developed than the other variable records.
- Could limit data to closed claims but ignores recent trends.
- Distribution shift could be change in coding over time (i.e., new code; change in code drop down options; practice). Fixed by recasting historical codes to current codes.
- Distribution shift in book between one type of attribute bucket to another needs to be addressed in some way or this attribute removed from modeling.

3. Split prepped data between training and testing hold out.

- Ensure split is random, and not biased.

- Good to also hold out last year of results from training to test model lands well on most recent year of data.

- Good to test that holdout is random, and not biased.

4. Create model at policy level, if applying tier factors at policy level. Better than class level since considers interaction between classes.

- Roll up class level records to policy
- Derive variables using class level detail rolled up to policy level.
- Append group level or other outside data sources.
- Create data dictionary for each variable including derived variables.
- Test attributes incl. derived variables for sample of policies against another source.

Derived Variable Examples

- Schedule rating factor.
- Difference between system proposed schedule rating factor and that applied by agent.
- Indicator of class payroll without employee counts.
- Average payroll per employee at policy level.
- Average payroll per employee and class level, calculate policy min, max, avg.
- Policy with no construction class payroll but with a prior construction loss.
- Prior loss count and loss dollars in past five years.
- Relativity of highest to lowest class rate on policy.
- Text mine claims data and identify policies with prior losses with safety issues.

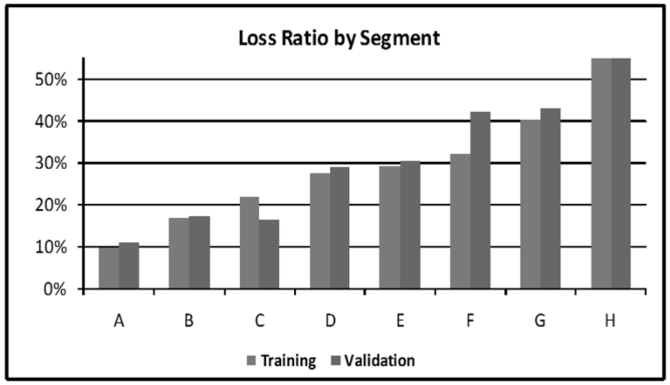
Sample Derived Variable List

Attribute Description	Derived (Y / N)	Policy Level Attribute
1. Policy Broker or Direct Indicator		Yes
2. Claims History		Yes
3. Policy Level Audited Payroll	Y	Yes
4. Estimated Exposure at Class Level		
5. New or Renewal	Y	Yes
6. Avg On-Level Premium per Employee per Class	Y	No
7. Avg On-Level Premium per Employee per Policy	Y	Yes
8. Avg Payroll per Employee per Class	Y	No
9. Avg Payroll per Employee per Policy	Y	Yes
10. Policy Prior Cancel Indicator (Y or N)		Yes
11. Whether Class Code was on Cash Business Class Code List	Y	No
12. Policy Claims Free Factor	Y	Yes
13. Class Claims Free Indicator	Y	No
14. Class Base Rate	Y	No
15. Class Description	Y	No
16. Commission Factor	Y	Yes
17. District Office Same as Servicing Office Indicator	Y	Yes
18. Dominant Class Code on Policy = Derived from Bureau's Definition of Dominant Class Code	Y	Yes
19. Dominant Industry Group on Policy = Derived from Bureau's Definition of Dominant Industry Group	Y	Yes
20. Employers Liability Limit	Y	Yes
21. Class Employee Count		No
22. Policy Level Highest Rated Class Code	Y	Yes
23. Policy Level Highest Class Base Rate	Y	Yes
24. Policy Level Relativity of Highest Class Code to Lowest Class Code Rate	Y	Yes

Over 70 attributes derived

5. Validate results with lift charts and other statistics.

Training Data					
Segment	Earned Exposures	OnLevel Earned Premium	Claim Count	Loss Ratio	Loss Ratio Relativity
A	12,077,278,517	786,452,383	4,392	10%	0.30
B	12,036,796,503	805,110,297	8,185	17%	0.52
C	14,645,672,425	633,750,315	9,086	22%	0.67
D	15,511,994,169	1,716,602,527	25,324	28%	0.84
E	14,806,846,351	982,944,860	16,832	29%	0.89
F	19,235,150,121	820,046,907	18,969	32%	0.98
G	15,758,325,350	1,124,833,045	24,623	40%	1.23
H	12,545,239,393	935,348,300	29,590	78%	2.38
Total	**116,617,302,829**	**7,805,088,634**	**137,001**	**33%**	**1.00**



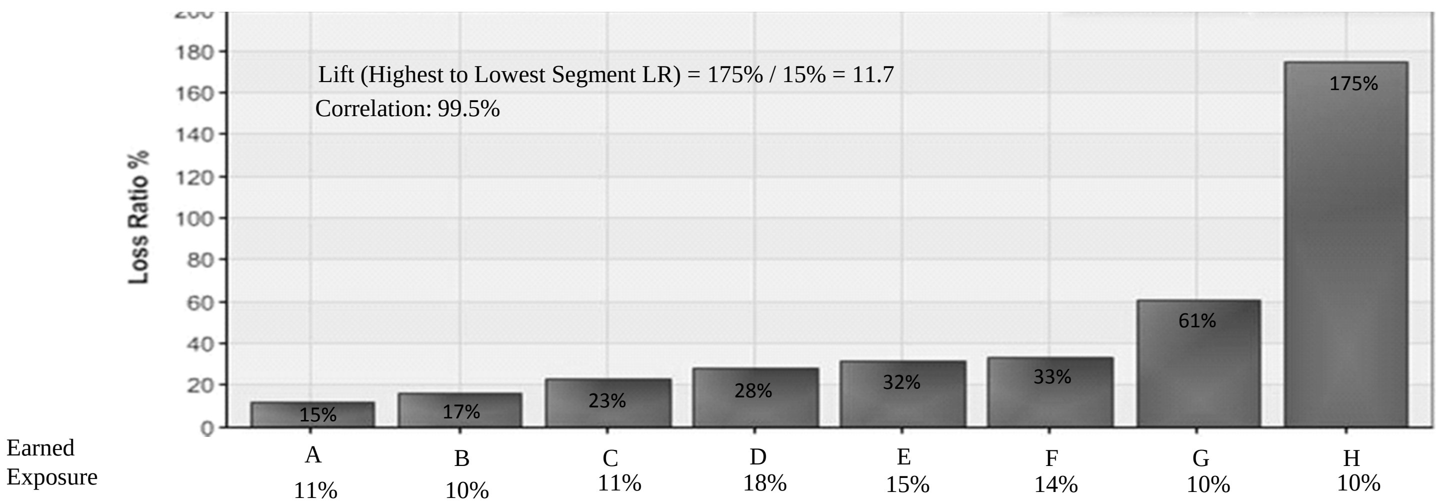
Validation Data					
Segment	Earned Exposures	OnLevel Earned Premium	Claim Count	Loss Ratio	Loss Ratio Relativity
A	5,187,175,908	337,131,585	1,889	11%	0.32
B	5,178,645,954	349,954,481	3,588	17%	0.50
C	6,106,267,771	270,367,244	3,928	16%	0.47
D	6,733,712,097	735,207,318	11,253	29%	0.84
E	6,477,569,186	424,433,740	7,517	30%	0.88
F	8,474,731,411	362,625,176	8,698	42%	1.22
G	6,605,407,108	479,775,601	10,501	43%	1.25
H	5,395,649,256	400,273,750	12,851	79%	2.29
Total	**50,159,158,691**	**3,359,768,895**	**60,225**	**34%**	**1.00**

Loss Ratio by Policy Year				
Segment	2006	2007	2008	2009
A	11%	9%	11%	8%
B	18%	19%	16%	15%
C	20%	21%	18%	22%
D	29%	33%	23%	22%
E	33%	29%	30%	23%
F	40%	29%	32%	41%
G	50%	42%	36%	33%
H	90%	88%	83%	48%
Total	35%	35%	32%	29%

Look at whether:

- Validation results similar to training results.
- Inversions within policy years.
- Segment definitions make sense and are implementable.

6. Review results with business stakeholders. Important to investigate every instance of disbelief and get buy-in before proceeding.

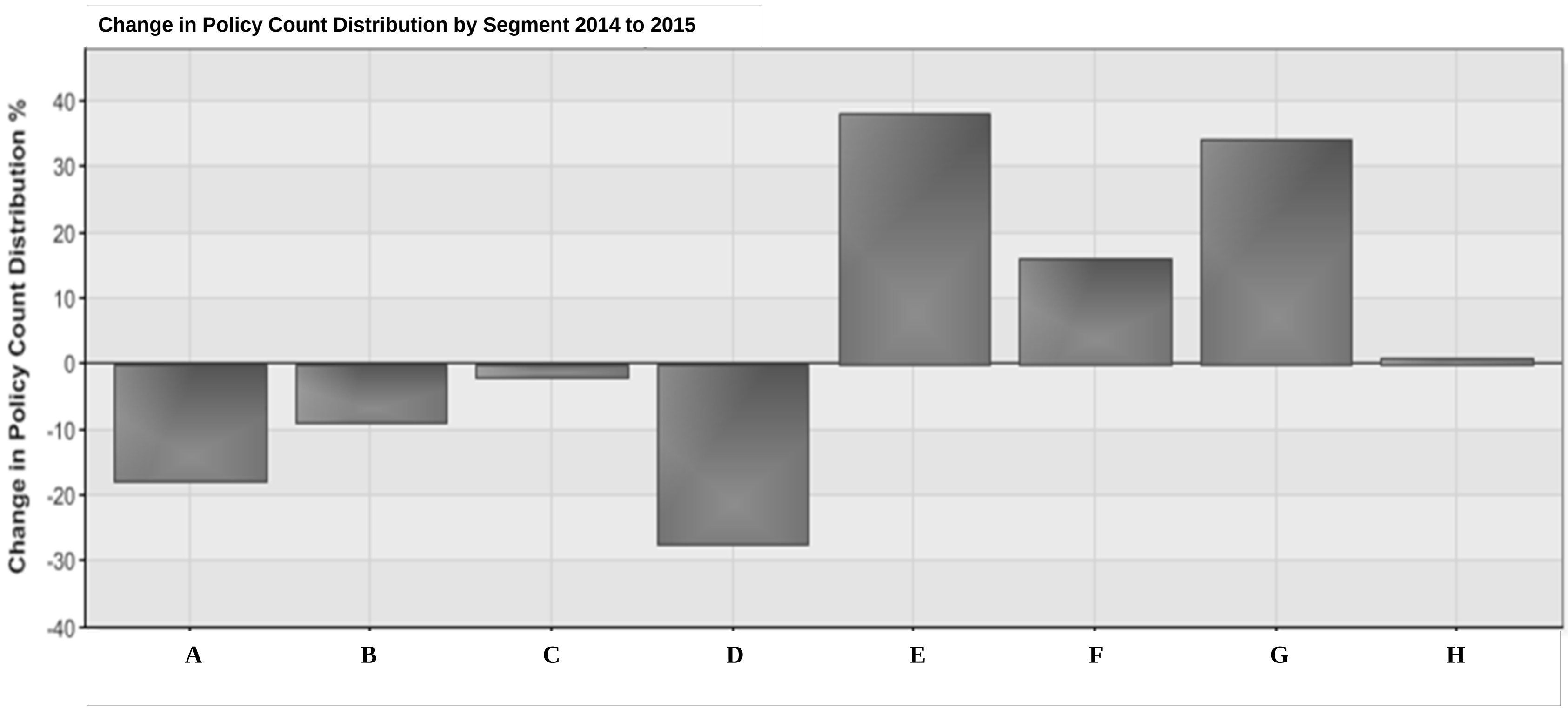


Present Life Charts But Start With Data Summary and Segment Definitions

Review Results – Data Summary by Segment

Segment Name	Loss Ratio	Exposure (Payroll)	Exposure Distribution	Earned Premium	EP Distribution	Reported L&ALAE	Loss Distribution	Claim Count	Claim Count Distribution	Avg Premium Per $100 Payroll	Frequency Per Payroll	Severity	Pure Prem. Per $100 Payroll
A													
B													
C													
D													
E													
F													
G													
H													
TOTAL													

Review Results – Change by Year



Volume of best 4 segments declined and worst 4 segments increased.

Review Results – Proposed Tiers

Tier	Earned Exposure 2011 - 2015	Reported Loss & ALAE Ratio 2011 - 2015	Indicated Relativity (Relative to Total)	Indicated Relativity (Relative to Middle)	Selected Relativity (Relative to Middle)
Best	25%	15%	.43	.75	.75
Middle	50%	20%	.57	1.00	1.00
Worst	25%	90%	2.58	4.50	3.00
Total	100%	35%			

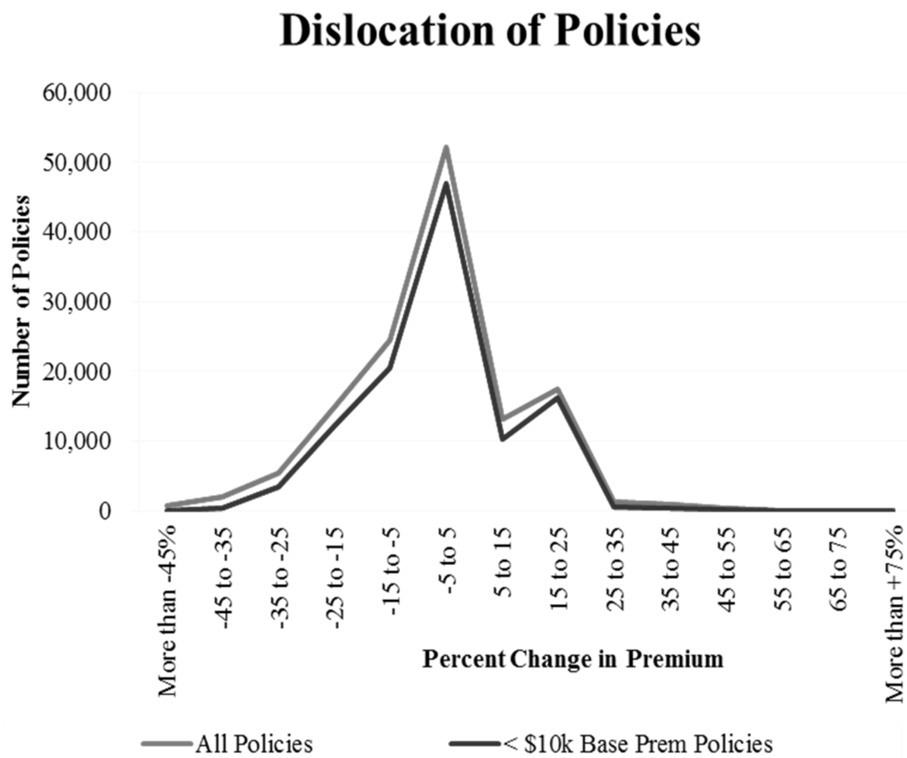
Would recommend more tiers to improve differentiation & reduce dislocation.

Review Results – Maps of Territory Relativities

Could also introduce or improve territorial definitions and factors

7. Determine How to Apply New Tiers

- Apply via schedule rating.
  - Easy IT implementation.
  - Less regulatory review.
  - Allows agent / underwriting intentional manipulation & unintentional skewing.
- Determine IT & other resource constraints to implement as new class plan factor and adjust as necessary.
- Calculate Dislocation & Obtain appropriate regulatory approval.



8. Roll-out plan, including communication to address resistance.

- Share results with agents and others, including segment definitions and results using attributes that are sensical. Do not just present a black box score with a result.

- Provide agents with list of policies with largest dislocations and go through a couple examples of why they are each getting large increases.

- Provide agents with overall rate change, so they understand it is just a wider range of rates and not an overall rate increase.

Using Text Mining to Fine Tune and Derive WC Predictive Model Variables

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Fine Tuning for Implementation

Situations will arise that are beyond the capture of information for the model

- Employer and workplace characteristics that are important indicators by without sufficient frequency for credible inclusion in models.
- There may be workplace programs or conditions that deserve special consideration when assigning an employer to a rating tier.
- There may be new workplace programs that are outside the time period captured in the predictive model.
- Underwriting reports, loss safety reports, and other text data may be a good source for such information.

Text-Mining for Ratemaking: General Considerations

- Starting requisite for being interested in text mining: Target information from text data not usually found in structured data or may take an extended time to get to structured data. (Example: time delay between when a medical service is provided and when it appears in the payment transactions.)

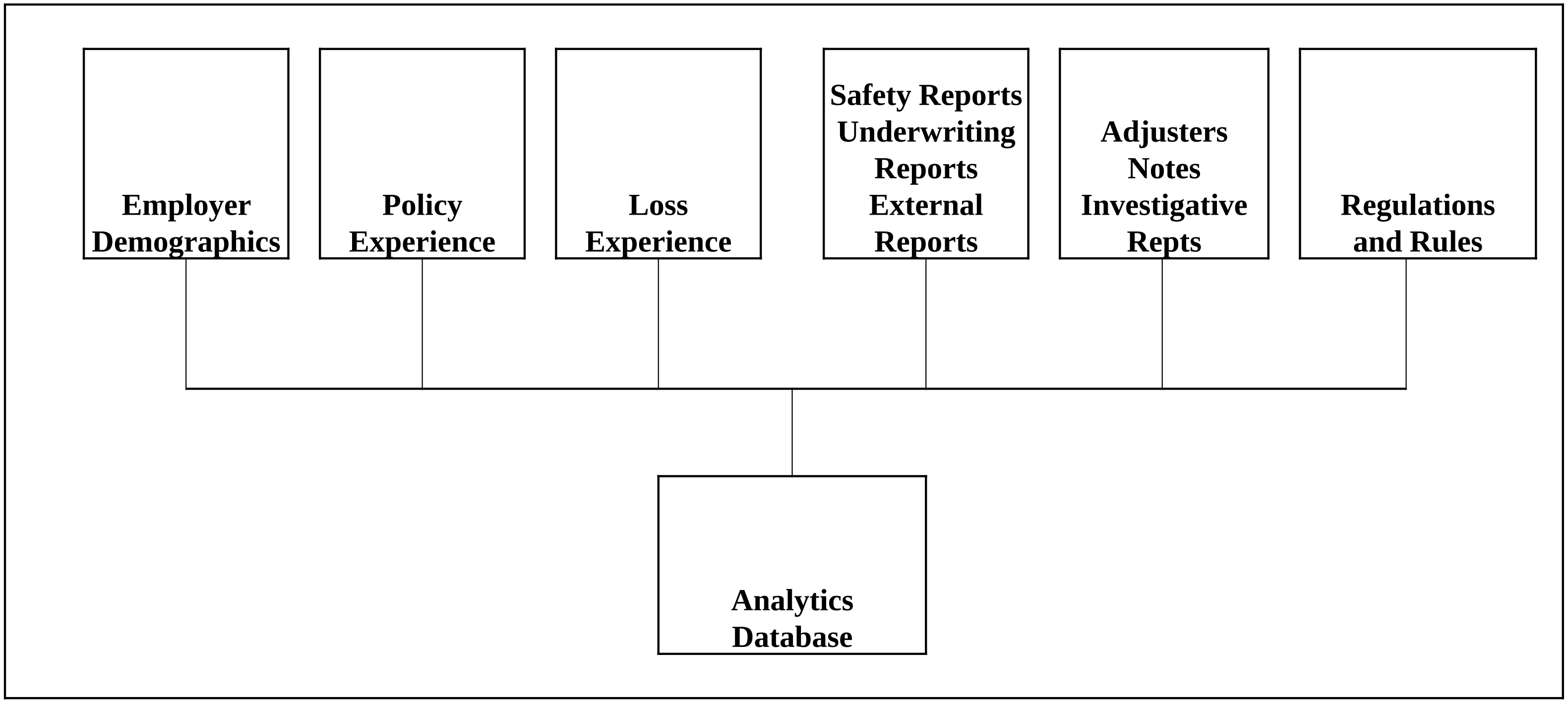
- In property-casualty insurance, text-mining has been most often associated with claims management (e.g., early identification of major medical treatments, attorney representation, co-morbidities).

- For ratemaking and underwriting, text-mining presents opportunities to supplement predictive modeling's ratemaking for potential adverse/favorable loss experience.

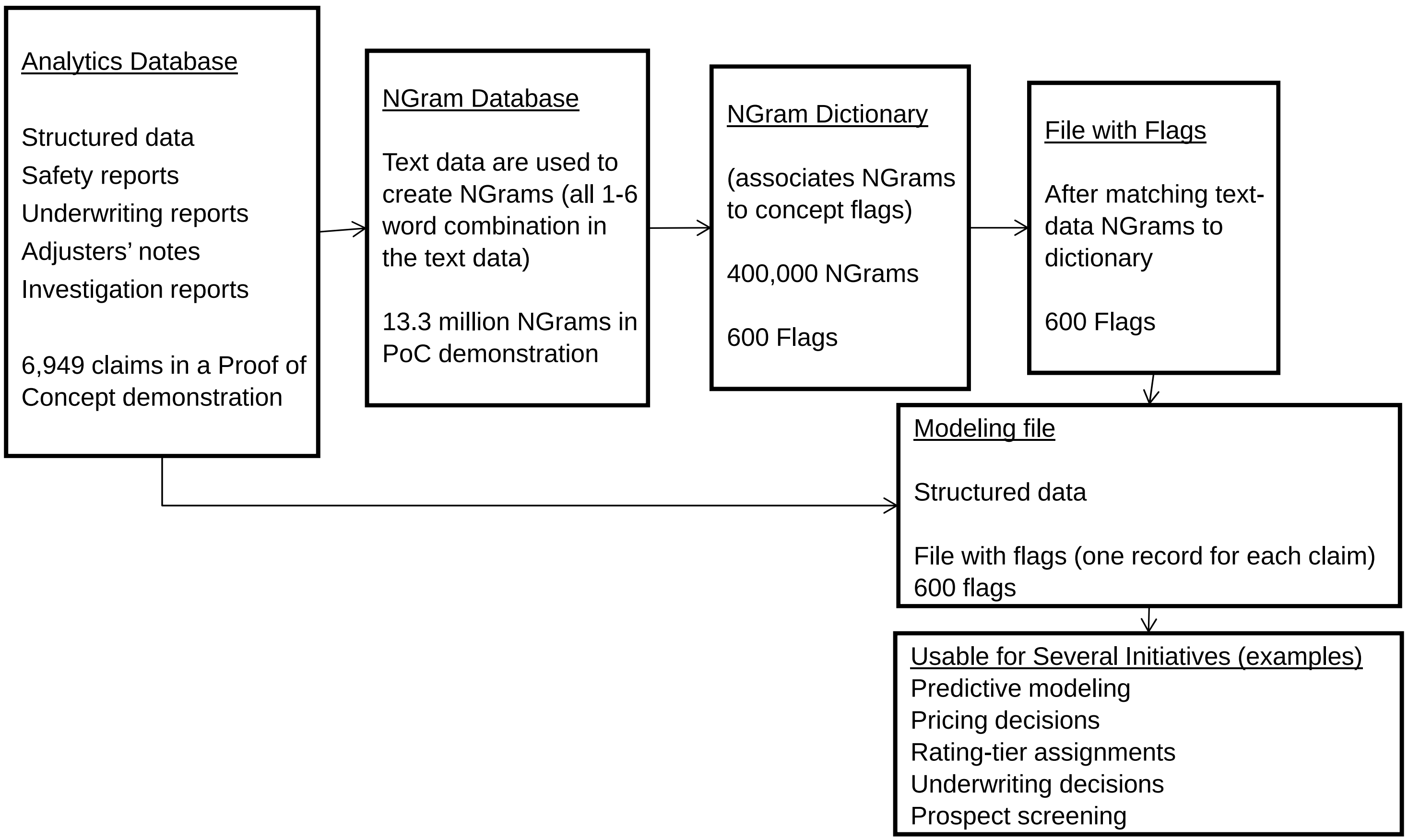
Text-Mining for Ratemaking: Sources of Information and Examples

- Sources of Information
  - Underwriting reports.
  - Loss Safety reports.
  - Accident descriptions (including at First Notice of Loss).
  - Claim adjuster notes.
- Examples of phrases that are found in text-form reports that could be signals for adverse/favorable experience.
  - “inadequate training”
  - “new training program”
  - “substandard lighting”, “poor vehicle maintenance”
  - “poor supervision”

Text-Mining for Ratemaking: Adding to the Analytics Database



Expanding Analytics Database to Include Information from Text-Mining



Text-Mining for Ratemaking: Uses of Text Data

- Variables in the predictive modeling.
  - Do not need high frequency, just sufficient number of references to be a differentiating variable.
- Business rules at implementation.
  - Number of references for a particular condition may be insufficient for credible modeling but sufficient for noteworthy exceptions.
  - Business rules could be developed to adjust an employer's rating tier up/down.
  - "New training program": may be a signal that an employer's loss experience will be better than the recent past (esp for experience model calculations)
  - "Inadequate training" could be used to disqualify an employer for a favorable rating tier.

Questions?

Thank you

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