

UCSB Probability & Statistics Actuarial Program



Presentation by
Roger M. Hayne,
Ph.D., FCAS, MAAA

CAS Annual Meeting
Orlando, FL
14 November 2016



Unique Actuarial Program at UCSB

The only Center of Actuarial Excellence on the West Coast and one of 17 CAE programs in US

- The most comprehensive program in CA
- **Unique 5-year combined program BS/MS in ActSci**
- Prize winning UG *Research Projects in Actuarial Science*
- UCSB Actuarial Program Advisory Board
- **Annual Actuarial Career Fair**
- **Annual Actuary Day**
- **Actuarial Visitor Program**
- Center for Financial Mathematics and Actuarial Research
- **California Actuarial Student Summit 2015, 2017**
- Courses cover 5 preliminary SOA/CAS exams
- SOA-approved courses for all VEE subjects



Actuarial Offerings

- Usual 4-year Bachelor degree in Actuarial Science
- Unique 5-year Master degree; a Masters for students with a UCSB Actuarial Science Bachelor degree for one additional year of graduate school
- Graduate program includes research (more of that later)



Undergraduate Actuarial Research

- Actuarial Research Projects:
 - 2010-2011: AAA NCNU
 - 2011- 2012: Towers Watson
 - 2012-2013: Solucia Inc.
 - 2012-2013: Towers Watson
 - 2013-2014: CSAA
 - 2013-2014: Towers Watson
 - 2013-2014: Blue Shield
 - 2014-2015: CSAA
 - 2014-2015: William Sansum Diabetes Center
 - 2015-2016: Vitality Group (Health & Fitness)
 - 2015-2016: Allstate (Auto; hand-held devices)
 - 2015-2016: Cottage Hospital (Readmissions)

Trend Analysis for Quarterly Insurance Time Series

Daniel Bortner, Cody Pulliam, Waiman Yam

Faculty Advisor: Michael Ludkovski

Department of Statistics and Applied Probability, University of California Santa Barbara



Abstract

Insurance companies commonly use **linear regression** to create predictive models by drawing a line of best fit through the data points. Here we are implementing the techniques of time series analysis to create a more accurate way to model quarterly data. Within the data, characteristics such as trend and seasonality can be utilized to improve upon basic **linear regression**. After comparing different models, the ARIMA model proves to be better at predicting the data than **linear regression**.

Objectives

- Explore whether time-series analysis is applicable to calculating future Pure Premium costs.
- Compare insurance firms' current **regression** forecasts to the time-series based methods.
- Identify which variables of the data provide more accurate predictions.
- Establish an effective methodology for forecasting.
- Compare the precision of different predictive models.
- Establish an effective methodology for forecasting.

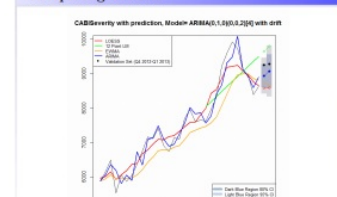
Data

- 18 States of Home Owners Policies (5 types of forms) and Auto Insurance Coverages (15 coverages) by quarter; Up to eight years (2005(1) to 2013(1)) worth of data and a maximum of 33 quarters per coverage/form.
- The data provided had already been applied a 4-quarter moving average.
- A 'series', denoted as a state and coverage (California -Bodily Injury), consists of their Frequency, Severity, Pure Premium, and Earned Exposure variables by quarter.
- Frequency = $\frac{\text{number of claims}}{\text{number of exposures}}$, the rate at which claims occur.
- Severity = $\frac{\text{total losses}}{\text{number of claims}}$, average cost of claims.
- Pure Premium = $\frac{\text{number of exposures}}{\text{number of exposures}} \times \text{Severity} \times \text{Frequency}$, the average loss per exposure, also known as the insurers expected risk per policy holder.
- Earned Exposure = Number of bookings for the quarter.

New Predictive Models

- Loss Smoothing** - Non-parametric regression methods that fits simple regression models to localized subsets of the data to build a function, found in R-Package(stats), using stl.
- EWMA** - Exponential Weighted Moving Averages Smoothing, found in R-Package(TTR), using EMA.
- ARIMA** - Combination of Auto-regressive and moving average smoothers, found in R-Package(forecast), using Auto.Arima

Comparing Models



- The term "12 Point" refers to number of most recent quarters used.
- Forecasts for each model are compared to the last two quarters of the original data (the Validation Set in black).

Citations, and Acknowledgments

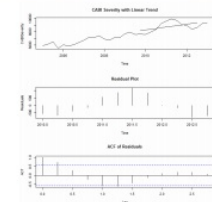
- Neter, John, William Wasserman, and Michael H. Kottner. Applied Linear Statistical Models. Homewood, IL: Irwin, 1996. Print.
- Brockwell, P. J. and R. A. Davis. Introduction to Time Series and Forecasting. 2nd ed. New York, NY: Springer, 2002.
- Jason Clark (2013). TTR: Technical Trading Rules. R package version 0.2-0. <http://CRAN.R-project.org/package=TTR>
- R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
- We would like to thank CSAA and our faculty advisor Mike Ludkovski for their assistance, guidance, and enthusiasm for this research.

Linear Regression

$$\hat{f}_t = b_0 + b_1 t + \epsilon_t \quad (1)$$

- Minimizes the amount of error between a best fit line and the actual data. Assumes residual component (ϵ_t) demonstrates random noise.
- Displays the overall trend of the data set.
- Regression** tends not to work well with volatile data.

Time Series Diagnostics



- Autocorrelation Function (ACF):**
- Forecast error is the distance between the predictions produced by the model and the last two quarters of the original data.
- Identifies which predictive model is closest to the Validation set.
- From the auto and home data sets, the forecast error is calculated for the Frequency, Severity, and Pure Premium variables in each series.
- Confidence intervals narrow when using ARIMA models versus the insurance firms' **regression** methods.

Results

Model	Reg.	Exponential Reg.	ARIMA	EWMA	Loss
Accuracy	0.0%	13.9%	38.9%	30.6%	16.7%

- Table shows percentage of how often a certain model has the lowest forecast error.
- Finding a seasonal component through autocorrelation proves Time Series analysis works well with data.
- ARIMA modeling best forecasts the insurance's Pure Premium.
- The Pure Premium is best estimated when forecasting the Frequency and Severity variables separate.



Undergraduate Actuarial Research

Auto Frequency Trend & Hand-Held Devices

Alex Hansen, Katherine Ozorio, John Torquato
Faculty Advisor: Janet Duncan

Department of Statistics and Applied Probability, University of California Santa Barbara



Abstract

During Phase I of our project, we concluded that accident frequency has been increasing in recent years and cell phone usage is at an all-time high. However, we were unable to establish a concrete positive correlation between the two, as there are many other confounding factors that also affect accident frequency. We created a model to estimate the impact that handheld devices have on auto accident frequency and auto premiums. This can be used to then estimate the potential savings of implementing an involuntary cell phone blocking device.

Phase I

- Auto insurance companies have been experiencing an uptick in auto accident frequencies since 2012. We compared cell phone use and auto accidents to estimate their relationship.
- According to industry data, auto accident frequency decreased from 2000-2012 and increased from 2012-2015. Normalizing for miles driven, the accident frequency flattens.
- Without the knowledge of in-vehicle use, cell phone data was more difficult to come by. We were able to find publicly available information on cell phone subscriptions which showed an increase over the last 20 years.
- The yearly increase in cell phone subscriptions was inconsistent with the decrease, and subsequent increase, in auto accident frequency. This could be due to other factors increasing and decreasing auto accident frequency over time, such as weather, car and road improvements, etc.

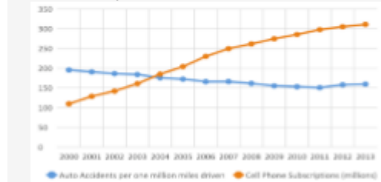


Figure 1: The number of police reported auto accidents per one million miles driven compared to cell phone subscriptions in millions in the United States from 2000-2015 (Source: U.S. Department of Transportation - National Highway Traffic Safety Administration; International Telecommunications Union)

Phase I Limitations

- We only used publicly available data which might not align with Allstate data
- Information on in-vehicle cell phone use was limited. One of the few metrics we were able to find was on the number of cell phone subscriptions.
- Inconsistencies of police reports record cell phone use.
- Multiple causes of accidents

Research Results

- In general, cell phones impact 1.12% of the auto premium. With a \$900 premium this translates to \$10.05.
- This analysis was based on "average" assumptions for drivers and auto premium. Limitations of publicly available data make it difficult to model the impact based on driver characteristics. However, some insurance companies may have more detailed data which could enhance a similar analysis.

Citations & Acknowledgments

NHTSA Study

- The purpose of this study was to investigate the effects of cell phone distraction.
- Data was collected from 204 drivers over 31 days in 2011.
- Only drivers who reported talking on a cell phone while driving at least once per day were recruited.
- Drivers were video recorded to analyze which type of cell phone activity was performed and how long it was performed for.
- Determined texting/browsing and looking for a cell phone when receiving a call were significantly dangerous.
- These activities accounted for 1.1% of driving time and increased the relative risk of an accident by 1.82 times.
- Using that, we determined that for cell phone users, 1.98% of accidents occur while being on the phone.
- Recorded in terms of safety critical events. In order to use this information, we assumed that the relative rate of accidents to safety critical events was independent of phone use.

Key Industry Figures

- AT&T Survey: Determined that 70% of people use their phone use driving. To make the definitions of phone use comparable, we made the assumption that people are unable to properly estimate their daily phone use and are either willing or not willing to use their phones while driving.
- Allstate Company Data: Looking at Allstate's annual and quarterly reports, we determined a loss ratio of 0.69 and an average premium of \$900.
- Insurance Information Institute: 12.6% of expected losses are from other than collision claims. We excluded these because they are not affected by phone use. This left us with 87.3% of expected losses are affected by phone use.

Model

Observed Driving Cell Phone Model		
a. Amount of crashes due to being on the phone by phone users	1.12%	\$900
b. "The cost of a phone being 2000 by phone users	\$200	\$200
c. Amount of premium that is not affected by phone use	\$700	\$700
d. Amount of premium that is affected by phone use	\$200	\$200
e. Amount of premium that is affected by phone use	\$200	\$200
f. Amount of premium that is affected by phone use	\$200	\$200
g. Amount of premium that is affected by phone use	\$200	\$200
h. Amount of premium that is affected by phone use	\$200	\$200
i. Amount of premium that is affected by phone use	\$200	\$200
j. Amount of premium that is affected by phone use	\$200	\$200
k. Amount of premium that is affected by phone use	\$200	\$200
l. Amount of premium that is affected by phone use	\$200	\$200
m. Amount of premium that is affected by phone use	\$200	\$200
n. Amount of premium that is affected by phone use	\$200	\$200
o. Amount of premium that is affected by phone use	\$200	\$200
p. Amount of premium that is affected by phone use	\$200	\$200
q. Amount of premium that is affected by phone use	\$200	\$200
r. Amount of premium that is affected by phone use	\$200	\$200
s. Amount of premium that is affected by phone use	\$200	\$200
t. Amount of premium that is affected by phone use	\$200	\$200
u. Amount of premium that is affected by phone use	\$200	\$200
v. Amount of premium that is affected by phone use	\$200	\$200
w. Amount of premium that is affected by phone use	\$200	\$200
x. Amount of premium that is affected by phone use	\$200	\$200
y. Amount of premium that is affected by phone use	\$200	\$200
z. Amount of premium that is affected by phone use	\$200	\$200

We made an adjustable model using our assumptions. This would allow a company to plug in their own numbers to see how much their policyholders could save.

Predictive Modeling of Healthcare Costs using Regression Trees

Daniel Mena, Alexandra Moat, Jessie Wang, Ian Duncan, Michael Ludkovski*

Department of Statistics & Applied Probability, UC Santa Barbara

*corresponding author: Tel.: +1-805-8935634

ludkovski@pstat.ucsb.edu

Abstract

The ongoing healthcare insurance reform under the Affordable Care Act (ACA) of 2010 makes it critical for insurers to engage in predictive modeling to control adverse selection and other concerns related to ACA. Few actuarial studies are currently publicly available on this subject. Using a unique dataset from a private insurer on 20,000 individuals we investigated predictability of next-year costs based on 133 current-year covariates for each covered member. Our predictor variables included basic demographic information, categorized insurance costs for current year, as well as over 80 Hierarchical Condition Categories (HCCs), listing medical conditions that triggered previous expenses. To tackle the large number of covariates and the highly nonlinear nature of healthcare costs, we utilized hierarchical statistical regression methods. In particular, we focused on Regression Trees (CART) and its extension Random Forests. A variety of different models, including gender-specific and demographics-only were fitted and validated. We also studied predictive power of the models for specific risk groups and statistical evidence regarding most important covariates. Our analysis shows that Random Forest is a promising method for predictive modeling, providing best performance across a range of other regression methods we tried. We also found that surprisingly HCCs carry little statistical significance compared to information about actual claims incurred. This work is related to Mackenzie, Sun and Wu (2013) who studied the same dataset using MARS regression.

An Example

Automobile Territories

- A project for a California insurer involved the use of statistical clustering methods to identify automobile rating territories
- Students applied three different methods, making use of insurer data and the R programming language
- Students also learned communication skills when they needed to present their results to insurer management at the insurer's offices
- They also presented their results in a poster session at UCSB's Undergraduate Research Colloquium
- Students visited the sponsoring company, submitted a written report and gave a presentation



UCSB Actuarial Advisory Board

Amy Yao, FSA, MAAA, Vice President & Chief Actuary, Blue Shield of CA, San Francisco.
Ben Flores '94, FSA, MAAA, Assistant Vice President, Pacific Life
Brett Horoff '91, ASA, ACAS, MAAA, Principal & Consulting Actuary, Perr & Knight
Cary Franklin '75, FSA, MAAA EA, Horizon Actuarial Services LLC
Diane Amarante '92, FSA, MAAA, Regional Vice President & Actuary, UnitedHealth Group
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Timothy Wilder, FSA, MAAA, Principal and Consulting Actuary, Milliman
William Kane '97, FSA, EA, Consulting Actuary, Towers Watson



UCSB Actuarial Association

ucsbactuary.org



- Job & internship recruitment
- Educational workshops
- Excel Workshops
- Resume Workshops
- Exam Reimbursement



2016-17 Actuary Association Officers



Actuary Day

The University of California, Santa Barbara Presents...

The 5th Annual **ACTUARY DAY** Friday, May 29th 2015

- 1:00 – 3:00 PM Student Project
- 3:00 – 3:15 PM Rama Thogarati Award
& New Officers Introduction
- 3:15 – 4:00 PM The Infinite Actuary:
Preparing for Actuarial Exams
- 4:00 – 4:30 PM Closing Reception



Located in the
Student Resource Building
Multipurpose Room
(SRB MPR)



Please bring your laptop that has the Excel program!



California Actuarial Student Conference 2015, 2017



CALIFORNIA ACTUARIAL
STUDENT CONFERENCE

April 4th, 2015
10 am - 5 pm
University of California, Santa Barbara

Network with fellow
aspiring actuaries and
listen to leaders of the
profession share their
experiences!

RSVP by March 10th at:
<http://www.pstat.ucsb.edu/CASC/2015>

ACTUARIAL ASSOCIATION OF UCSB





ARC 2014 Hosted by UCSB





Poster Prize Winner ARC 2014

- One among many student research projects
- Considered measurement of trend using quarterly data
- Presented as a poster session at the 2014 Actuarial Research Conference
- Was awarded first prize (jointly) for poster sessions

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Time Series Diagnostics

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 - Severity = $\frac{\text{total amount of claims}}{\text{number of claims}}$, average cost of claims.
 - Pure Premium = $\frac{\text{total amount of claims}}{\text{number of policyholders}}$ = Severity \times Frequency, the average loss per exposure; also known as the insurers expected risk per policy holder.
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New Predictive Models

- **Loess Smoothing** - Non-parametric regression methods that fit simple regression models to localized subsets of the data to build a function, found in R-Package(stats), using `spl`.
- **EWMA** - Exponential Weighted Moving Average Smoothing, found in R-Package(TTR), using `EMA`.
- **ARIMA** - Combination of Auto-regressive and moving average smoothers, found in R-Package(forecast), using `AutoARIMA`.

Comparing Models

- The term "12 Point" refers to number of most recent quarters used.
- Forecasts for each model are compared to the last two quarters of the original data (the Validation Set in black).

Antocorrelation Function (ACF)

- Residual component shows does not reflect a random process, hence there is unexplained dependence, possibly a seasonal component.
- The ACF calculates the correlation at different lag intervals to help identify any dependence within the data (i.e. Lag 1 = One year).
- If lags in the ACF exceed the confidence interval (blue dashed line), the process is non-stationary, and thus is used in the ARIMA model to capture the dependent lag with high autocorrelation.
- Many of the series also resulted in a strong autocorrelation at lag 1, indicating a seasonal component at one year.

Forecast Error

- Forecast error is the distance between the predictions produced by the model and the last two quarters of the original data.
- Identifies which predictive model is closest to the Validation set.
- From the suite and lower data sets, the forecast error is calculated for the Frequency, Severity, and Pure Premium variables in each series.
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Citations, and Acknowledgments

[1] Peter, John, William Wasserman, and Michael H. Kotner. Applied Linear Statistical Models. Harwood, IL: Irwin, 1999. Print.
 [2] Brockwell, P. J. and R. A. Davis. Introduction to Time Series and Forecasting, 2nd ed. New York: Wiley, Springer, 2002.
 [3] Joshua Ulrich (2013). TTR, Technical Trading Rules. R package version 0.226. <http://CRAN.R-project.org/package=TTR>
 [4] R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.
 • We would like to thank CNA and our faculty advisor Mike Ludkovski for their assistance, guidance, and enthusiasm for this research.



Taking Advantage of CAS Opportunities

- UCSB students have consistently taken advantage of CAS opportunities when available
- A contingent of UCSB students attended student sessions at the 2014 CLRS
- UCSB students are frequent visitors at meetings of the Southern California Casualty Actuaries Club
- UCSB students took advantage the convenient location of ARC 2014 to both attend and participate



2016
Actuarial Career
Fair

