### Sentiment Score Analysis of Establishment Survey Interviewer Notes Proof of Concept and Preliminary Results

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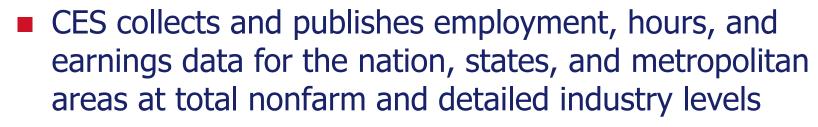
### **Overview**

- CES Overview CATI Data Collection and Notes
- Sentiment Analysis Proof of Concept (R and SAS)
- Preliminary Results
- Conclusions/Going Forward



### **Background on the Current Employment Statistics Survey**

- The BLS Current Employment Statistics (CES) survey is also known as the payroll survey or the establishment survey
- The CES Survey is a monthly multi-modal survey of establishments
  - Survey of about 143,000 businesses and government agencies, representing approximately 588,000 individual worksites





# Computer Assisted Telephone Interviewing

- 26% of CES reports are collected by CATI. We also use other methods like web and fax
- Interviewers at Data Collection Centers (Atlanta, Dallas, Kansas City, and Fort Walton Beach) call respondents and collect data using CATI software
- CATI software allows interviewers to take notes, schedule call times, and review reported data



# **Project Background**

- CES is required to permanently save CATI interviewer notes
- CATI interviewer notes contain valuable, qualitative information about businesses participating in the CES survey
- Data mining techniques such as sentiment analysis may be used to quantify information contained in the notes



# Sentiment Analysis Explained

### Estimating sentiment

- Many complex algorithms have been developed – all are limited by the computer's ability to interpret language
- Pros: facilitates analysis of millions of text notes in a short period of time
- Cons: computers will incorrectly interpret nuanced phrases, sarcasm, etc.



## **Project Methods**

- This project used an algorithm that counts the number of "positive" and "negative" words and computes an overall sentiment score for each note
- This analysis used a list of positive and negative words categorized by researchers Hu and Liu in their "opinion lexicon" of about 6,800 words
- The project was a proof of concept exercise and only analyzed notes from Wisconsin businesses. A total of 61,000 interviewer notes were used
- Sentiment Scoring code was developed by CES staff in both SAS and R; both software systems produced matching results



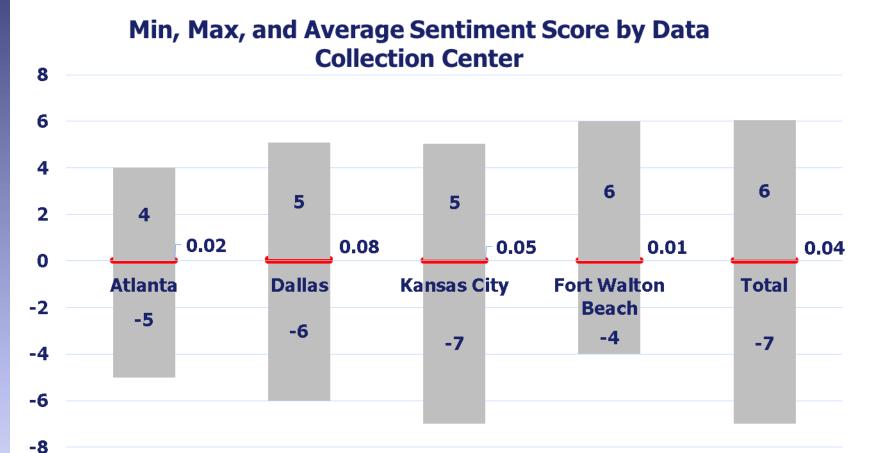
# Sentiment Scoring Example

#### Example Note:

Respondent called and was a little **nervous** that she had submitted the data **wrong**. I walked her through it and she did a **great** job. She said she **likes** to call in when she is doing the payroll as it is **easier** for her. I reassured her she is doing a **great** job. Scheduled for May and I let her know we send reminder post cards before the appointment we made and she said that was **great**.

<b>Positive Word Count</b>	Negative Word Count	Calculated Sentiment Score		
5	2	3		

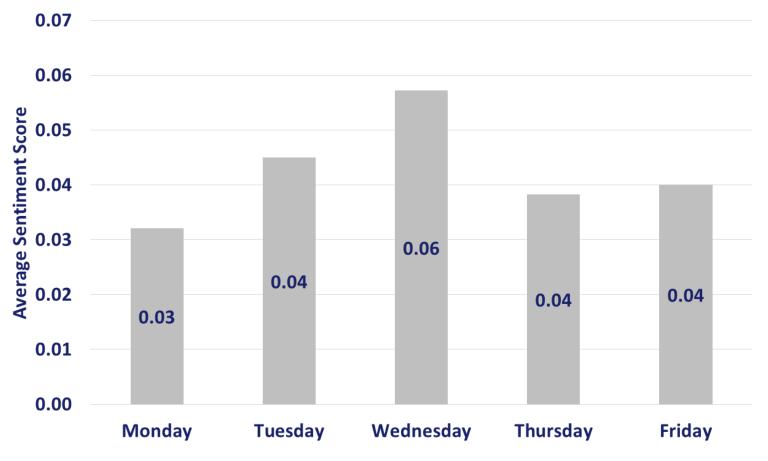






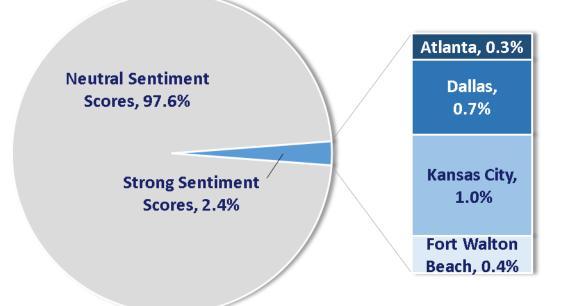


#### **Average Sentiment Score by Day of the Week**



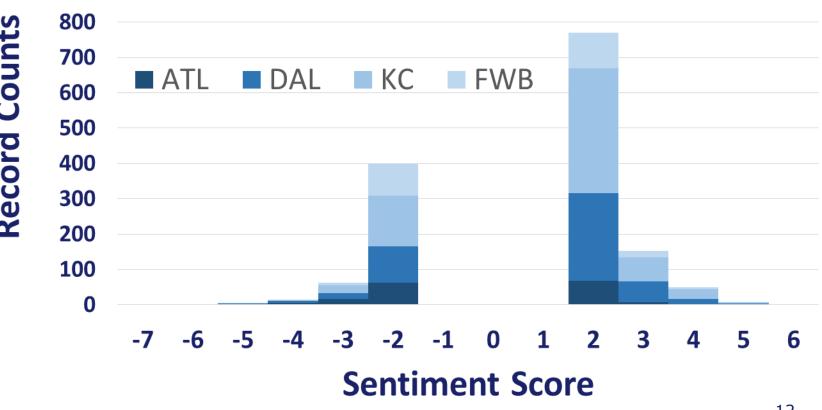
### Sentiment scores are mostly "neutral" (zero, 1, or -1)

Percentage of Records with Neutral vs. Strong Sentiment Score (Strong Sentiment Scores Broken Out by Call Center)





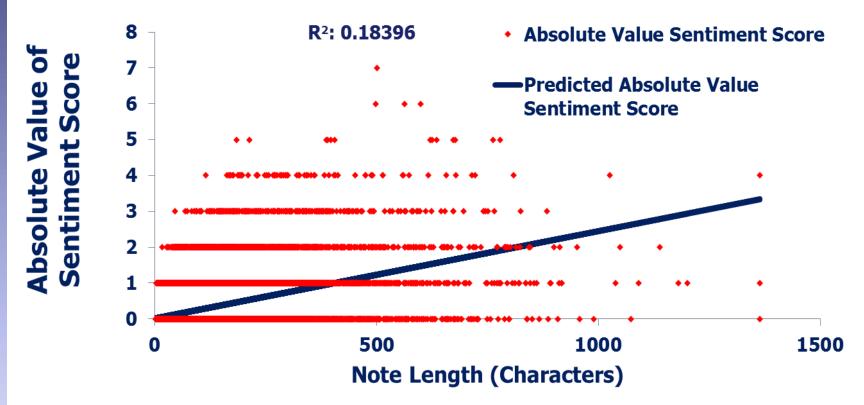
### Sentiment Score Distribution by Call Center, excluding "neutral" scores of 1, 0, and -1



**Record Counts** 

900

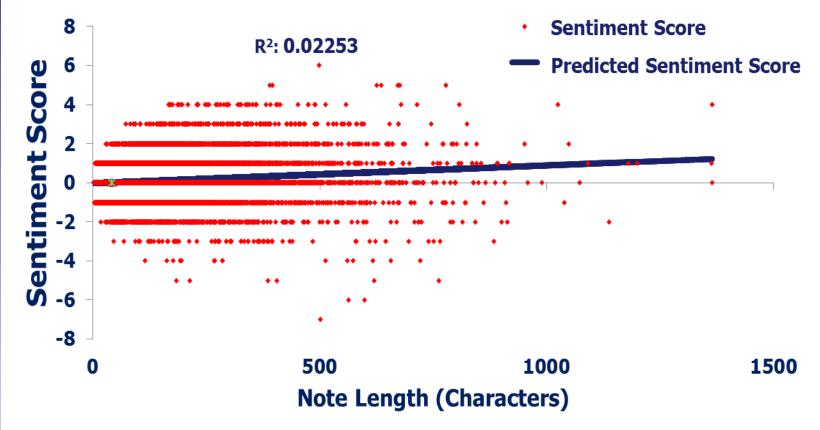
#### **Strength of Sentiment Score vs. Note Length**





\*Longer notes are more likely to have a "strong" sentiment score

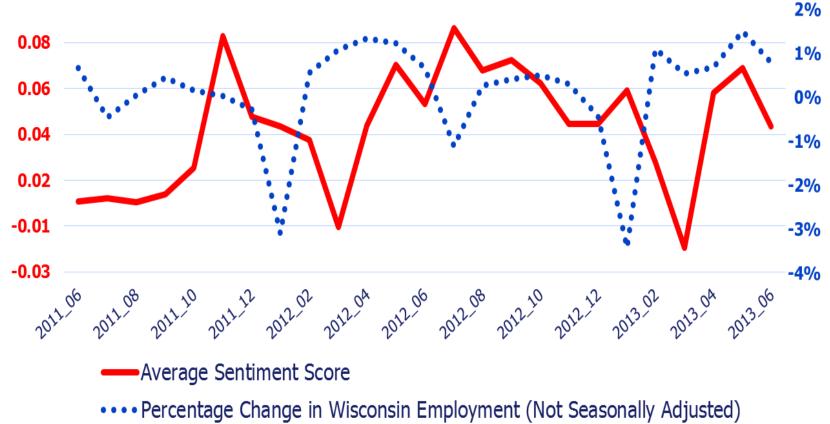
#### **Sentiment Score vs. Note Length**





\*Longer notes are also more likely to have a positive sentiment score 14

Average Sentiment Score vs. Percentage Change in Wisconsin Employment (Not Seasonally Adjusted)





### Conclusions

- Our preliminary sentiment score proof of concept was successful
- Sentiment analysis allowed us to quantify information from existing CATI notes
  - Old notes had previously been taking up storage space with unusable qualitative information
- Sentiment analysis algorithms can be applied to existing qualitative BLS data at low cost/resources



# **Going Forward**

- Expand this research to other states and time periods for further analysis
- More targeted/complex algorithms
  - Creating a CES specific "positive" and "negative" word list
  - Using a scaling system (degree of negativity/positivity of each word)
  - Seasonally adjust Sentiment Scores to compare with seasonally adjusted CES data



# **Going Forward**

- Discern whether respondent or interviewer sentiment is being detected
  - Geographical analysis of business location vs.
    Data Collection Center location
- Potential Applications:
  - Collection rate evaluation
  - Survey non-response, late response, and targeting collection time



### **Contact Information**

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www.bls.gov

### Appendix

Analysis was done on a sample of about 61,000 notes from Wisconsin
 Stats by call center:

Averages by Call Center										
Call Center	Min Score	Avg Score	Max Score	Avg Length	Max Length	Strong Sentiment	Total Record Count	% with Strong Sentiment		
Atlanta	-5	0.02	4	74	958	163	7404	2.2%		
Dallas	-6	0.08	5	86	1200	455	13451	3.4%		
Kansas City	-7	0.05	5	69	1364	618	28581	2.2%		
Fort Walton Beach	-4	0.01	6	58	1049	229	11686	2.0%		
Total	-7	0.04	6	71	1364	1465	61122	2.4%		

