HUSSMAN SCHOOL OF JOURNALISM AND MEDIA

Electrical and Computer Engineering

Transformer- and Lexicon-Based Sentiment Analysis (TLSA) as a **Real-Time** Web Service

Xinyan (Eva) Zhao, School of Journalism and Media, University of North Carolina at Chapel Hill

Chau-Wai Wong, Electrical and Computer Engineering, North Carolina State University

Background

- Computational tools have been introduced to communication research (Hilbert et al., 2019; van Atteveldt & Peng, 2018).
- Three challenges:
  - Slower adoption in communication science (programming training).
  - Uneven distribution of tools in application (deep learning uncommon).
  - Lack of measurement validity of the tools (accuracy concern).

Our Aim

Promote valid, open, and affordable automated measures of sentiment & emotions through a free real-time web service.

Automated Measures of Emotions & Sentiment

Existing Tools

Word-based: Linguistic Inquiry and Word Count (LIWC; Tausczik & Pennebaker, 2010), NRC lexicon (Mohammad & Turney, 2013).

Traditional machine learning (ML) models: Support vector machine (SVM), Naïve Bayes, (shallow) fully-connected neural networks.

Deep learning models: Convolutional neural network (CNN), recurrent neural network (RNN), transformer models (e.g., BERT).

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Sentiment & Emotions Lexicons

Lexicon 1: **NRC**	*Lexicon 2*: **AFINN**	*Lexicon 3* : **BING**
Binary categorization PLUS emotions	numeric score between -5 & 5	binary categorization

```
# A tibble: 26,943 x 3
   gutenberg_id       word    sentiment
          <int>      <chr>        <chr>
 1          768      visit     positive
 2          768  beautiful          joy
 3          768  beautiful     positive
 4          768      fixed        trust
 5          768 completely     positive
 6          768    perfect anticipation
 7          768    perfect          joy
 8          768    perfect     positive
 9          768    perfect        trust
10          768   suitable     positive
# ... with 26,933 more rows
```

```
# A tibble: 6,284 x 3
   gutenberg_id          word score
          <int>         <chr> <int>
 1          768      troubled    -2
 2          768     beautiful     3
 3          768       perfect     3
 4          768        heaven     2
 5          768       jealous    -2
 6          768        honour     2
 7          768          hope     2
 8          768   interrupted    -2
 9          768 inconvenience    -2
10          768    determined     2
# ... with 6,274 more rows
```

```
# A tibble: 7,974 x 3
   gutenberg_id          word sentiment
          <int>         <chr>     <chr>
 1          768      troubled  negative
 2          768     beautiful  positive
 3          768       perfect  positive
 4          768        heaven  positive
 5          768      suitable  positive
 6          768    desolation  negative
 7          768  suspiciously  negative
 8          768       jealous  negative
 9          768  perseverance  positive
10          768 inconvenience  negative
# ... with 7,964 more rows
```

https://datacritics.com/2018/03/14/three-text-sentiment-lexicons-in-r-tidytext/

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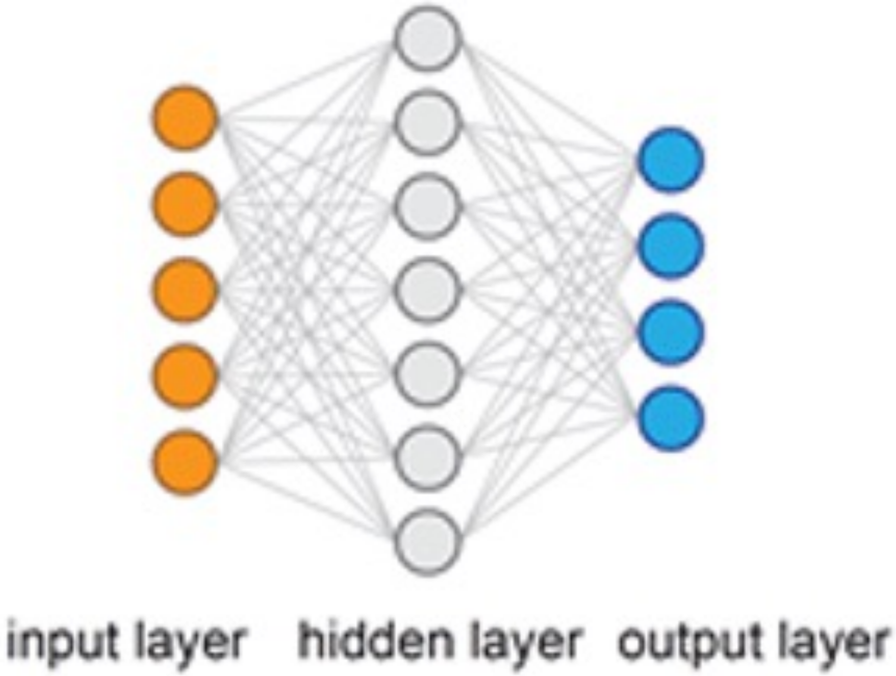
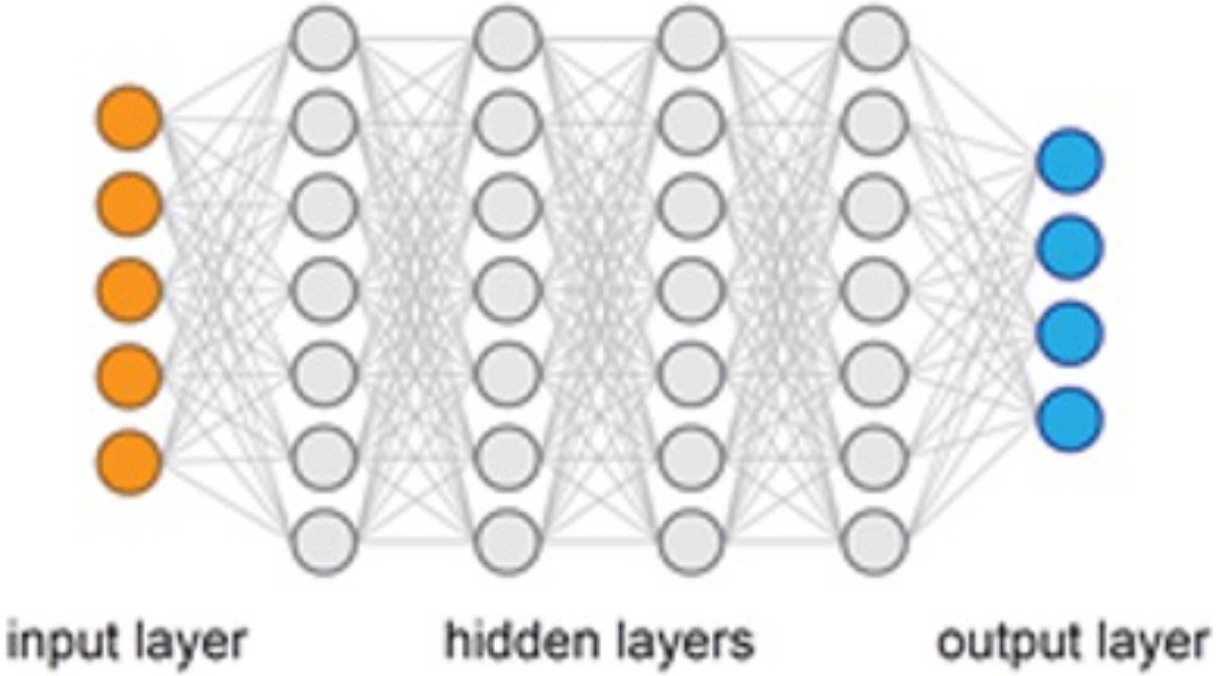
Shallow Neural Network vs. Deep Neural Network





Traditional

Modern

Why is Deep Learning so Successful?

1. **Improved model:** convolutional layer, more layers ("deep"), simpler activation (i.e., ReLU), skip/residual connection (i.e., ResNet), attention (i.e., Transformer)
2. **Big data:** huge dataset, transfer learning
3. **Powerful computation:** graphical processing units (GPUs)

- Example of big data: ImageNet (22K categories, 15M images)

Deng, Dong, Socher, Li, Li & Fei-Fei, "ImageNet: A Large-Scale Hierarchical Image Database," *IEEE CVPR*, 2009.

Tools Integrated by TLSA

Traditional

Dictionaries/Lexicons		
NRC	General	8,883 words (1,837 negative, 3,653 neutral, and 1,542 positive words)
AFINN	Microblogs, Tweets	2,477 words (1598 negative, 878 positive words)
Loughran McDonald	Financial documents, earning calls	2,690 words (2,337 negative, 353 positive words)
VADER	Social media, product reviews, opinion editorials	7,500 words. A dictionary + rule-based heuristics.
TextBlob Sentiment	Web content	5,750 adjective words from Pattern. Also provides a NLTK-based Naïve Bayers (NB) Classifier.

Modern

Transformer-based Models		
BERTweet Sentiment	Tweets (SemEval 2017 corpus)	A fine-tuned model trained with ~40k tweets. The base model is BERTweet, a RoBERTa model.
DistilBERT base uncased finetuned	General, movie reviews	A fine-tuned model trained with ~70k phrases from Stanford Sentiment Treebank (SST2). The base model is DistilBERT-base-uncased.
Twitter Roberta base sentiment	Tweets	A fine-tuned model trained with ~58M tweets. The base model is RoBERTa.

Transformer- and Lexicon-Based Sentiment Analysis (TLSA)

http://tlsa-service.ddns.net:5000/

Step 1: Fill in the CSV template on your local computer.

Note: The "text" column is required whereas the "label" column is optional. If the "label" column is filled in, it can be treated as the reference and the predictive quality be evaluated accordingly.

Step 2: Select your CSV file.

Choose File No file chosen

Step 3: Do you want to include the predictive quality evaluation? ○ **Yes** ◉ **No**

Step 4: Process and Download

Get a cup of coffee 😃 It may take up to 1 minute for the processed files to be ready for downloading.

Zhao, X., & Wong, C.-W. (2022). Automated Measures of Sentiment via Transformer- and Lexicon-Based Sentiment Analysis (TLSA). TechRxiv. https://doi.org/10.36227/techrxiv.21781109.v1

Input: Data Format

Input Text (Required)	Category (Optional)
@GovRickSnyder Must Be Prosecuted 4 Negligence #Flint Poisoning 4 Sake of @MiGov fascist master's profits http://www.addictinginfo.org/2015/10/09/emerg	Negative
8,000 Flint Residents Face Eviction For Refusing To Pay For Contaminated..Water #FlintWaterCrisis this is a Crime RT ...	Negative
ABSOLUTE BULLSHIT..Must be a way to prosecute the folks...LEAD POISONING IS IRREVERSIBLE...#FlintWaterCrisis https://twitter.com/HectorSolon/status/652	Negative
Would Michigan have been ok with this if it were Bloomfield Hills? Unbelievable. Love to Flint citizens. #flintwater https://twitter.com/howardlfuller/status/682	Neutral
@uspirg @reevynap @yananw #michigan damage already done; shame on Gov Synder for using #FlintWater to get fed money for murdering kids body	Negative
@dankildee On #Flint Water Crisis: 'There Was Incompetence At The Very Least" http://detroit.cbslocal.com/2015/12/30/kildee-on-flint-water-crisis-there-was	Negative
Great article on #FlintWaterCrisis highlighting key role played by @MonaHannaA. https://www.rt.com/usa/327363-flint-children-blood-lead-water/√Ç¬†√¢¬Ä¬¶	Positive
How horribly awful is that reality! 😢❗ #Flintwater	Negative
They KNOWINGLY POISONED the people of #Flint. :-(Flint toxic water tragedy points directly to Michigan Gov. Snyder http://www.msnbc.com/rachel-maddow-	Negative
Flint Michigan has a manmade disaster. Children are bing poisoned by lead in water. #FlintWater	Negative
#FlintWater crisis personifies the tragic effects of environmental health disparity.	Negative
@MMFlint Why don't you talk/tweet/rant daily about #Flint TERROR? A city full of children permanently poisoned by Republican apathy. #Water	Negative
@LittleMissFlint HAPPY BIRTHDAY, SWEETIE! You are an inspiration to millions. And you never let us forget! #FlintWaterCrisis #FlintWater	Positive
For $100M spent on missles, we could have stopped *US* children from being poisoned & built something rather than destroy #FlintWaterCrisis	Neutral
Chemicals poisoning people due to the #FlintWaterCrisis should be the concern of @realDonaldTrump NOT any real or imagined attacks in #syria	Negative
WTF is wrong with @IAmSteveHarvey? Hes on a downward spiral and he doesnt even know it. #FlintWaterCrisis	Negative
Lyons' failure to act led to at least 1 death + who knows how many hundreds injured/sickened. #FlintWaterCrisis	Negative
Thank you to all who participated in any way to #Resist #DAPL & support #FlintWater We can do this together There is worldwide support	Positive
Amazing we really are a country of laws. Hope the hope. #Flint #FlintWaterCrisis	Positive

1st Output: Accuracy Metrics

	Accuracy	Kappa	Neg-Precisior	Neg-Recall	Neg-F1	Neg-Size	Neu-Precisior	Neu-Recall	Neu-F1	Neu-Size	Pos_Precisior	Pos-Recall	Pos-F1	Pos-Size
afinn	0.72	0.51	0.87	0.9	0.88	51	0	0	0	18	0.51	0.9	0.66	21
nrc	0.54	0.29	0.86	0.61	0.71	51	0.19	0.28	0.22	18	0.48	0.62	0.54	21
lm	0.52	0.25	0.85	0.65	0.73	51	0.16	0.28	0.2	18	0.45	0.43	0.44	21
vader	0.72	0.51	0.87	0.9	0.88	51	0	0	0	18	0.51	0.9	0.66	21
textblob	0.56	0.33	0.93	0.55	0.69	51	0.22	0.22	0.22	18	0.43	0.86	0.57	21
bertweet	0.77	0.59	0.87	0.92	0.9	51	0.38	0.17	0.23	18	0.68	0.9	0.78	21
distilbert	0.76	0.55	0.82	0.98	0.89	51	0	0	0	18	0.62	0.86	0.72	21
twitterroberta	0.74	0.56	0.92	0.9	0.91	51	0.27	0.17	0.21	18	0.62	0.86	0.72	21

2nd Output: Sentiment Scores

D	E	F	G	H	I	J	K	L	M	N	O	P	Q
afinn_score	afinn_label	afinn_norma	nrc_score	nrc_label	lm_score	lm_label	vader_score	vader_label	textblob_sco	textblob_lab	bertweet_la	distilbert_lal	twroberta_lal
-4	Negative	-0.0664455	1	Positive	0	Neutral	-0.7964	Negative	0	Neutral	Negative	Negative	Neutral
-9	Negative	-0.1495025	0	Neutral	-0.9999997	Negative	-0.8625	Negative	0	Neutral	Negative	Negative	Negative
-6	Negative	-0.0996683	-0.25	Negative	-0.3333332	Negative	-0.8038	Negative	0.2	Positive	Negative	Negative	Negative
2	Positive	0.03322277	0	Neutral	0	Neutral	0.802	Positive	0.25	Positive	Negative	Positive	Negative
-8	Negative	-0.1328911	-0.0714286	Negative	-0.999999	Negative	-0.891	Negative	0	Neutral	Negative	Negative	Negative
-10	Negative	-0.1661139	0	Neutral	-0.9999998	Negative	-0.8126	Negative	-0.39	Negative	Negative	Negative	Neutral
3	Positive	0.04983416	0	Neutral	0.9999995	Positive	0.7579	Positive	0.4	Positive	Positive	Positive	Positive
-3	Negative	-0.0498342	-0.3333333	Negative	0	Neutral	-0.8687	Negative	-1	Negative	Negative	Negative	Negative
-12	Negative	-0.1993366	-0.4	Negative	-0.9999997	Negative	-0.8964	Negative	-0.325	Negative	Negative	Negative	Negative
-4	Negative	-0.0664455	-0.0833333	Negative	0	Neutral	-0.8074	Negative	0	Neutral	Negative	Negative	Negative
-5	Negative	-0.0830569	-0.5	Negative	-0.4999999	Negative	-0.7964	Negative	-0.75	Negative	Negative	Negative	Negative
-11	Negative	-0.1827253	-0.1111111	Negative	0	Neutral	-0.8602	Negative	0.175	Positive	Negative	Negative	Negative
4	Positive	0.06644555	0	Neutral	0.9999995	Positive	0.9327	Positive	1	Positive	Positive	Positive	Positive
-6	Negative	-0.0996683	-0.3333333	Negative	-0.9999995	Negative	-0.8225	Negative	-0.15	Negative	Negative	Negative	Negative
-1	Negative	-0.0166114	0	Neutral	-0.999999	Negative	-0.7717	Negative	0.0375	Positive	Negative	Negative	Negative
-6	Negative	-0.0996683	-1	Negative	-0.9999995	Negative	-0.824	Negative	-0.5	Negative	Negative	Negative	Negative
-6	Negative	-0.0996683	-0.1818182	Negative	-0.9999995	Negative	-0.802	Negative	-0.0388889	Negative	Negative	Negative	Negative
6	Positive	0.09966832	0	Neutral	0	Neutral	0.7845	Positive	0	Neutral	Positive	Positive	Positive
8	Positive	0.1328911	0.2	Positive	0	Neutral	0.8625	Positive	0.4	Positive	Positive	Positive	Positive

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