INTRODUCTION TO NATURAL LANGUAGE PROCESSING

THEORY AND APPLICATION FOR ENGINEERING

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Knowledge Extraction and Application Project

Systems Integration Division

Engineering Laboratory

National Institute of Standards and Technology

U.S. Department of Commerce

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BACKGROUND: PROJECT/PROGRAM OVERVIEW

Knowledge Extraction *and* ***Application***

- Much of manufacturing know-how is computationally inaccessible, within informally-written documents
- Create human-centric data pipelines to extract value from existing unstructured data at minimal labor cost
- Develop guidelines for using semi-structured data in KPI creation, functional taxonomy prediction, and customized worker training paths

BACKGROUND: MAINTENANCE WORK-ORDER DATA

"HP coolant pressure at 75 psi"

"Hyd leak at saw atachment"

"Major hydraulic leak at Sp#6 horseshoe"

"Clamping spool guard broken"

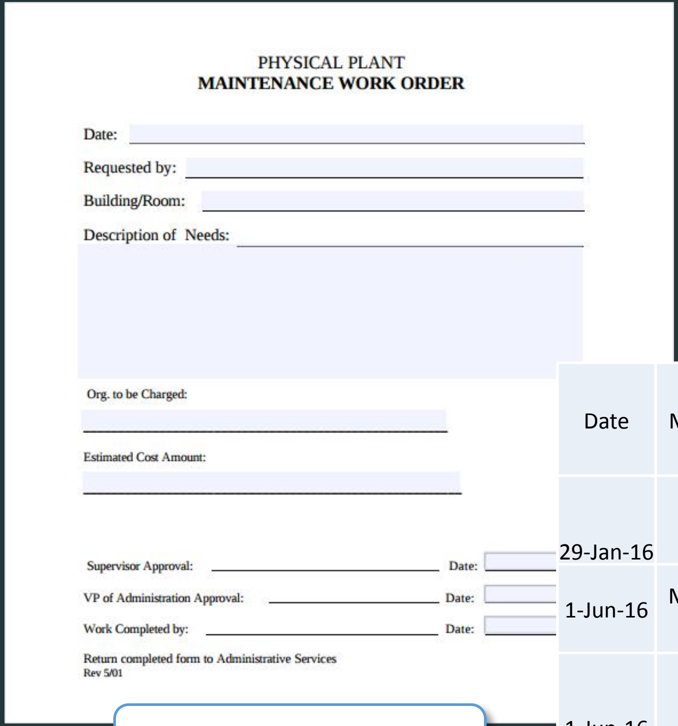
"Replaced seal in saw attachment but still leaking – Reapirs pending with ML"

"Bad Gauge / Low pressure lines cleaned ou"

"Replaced – Operator could have done this!"

"Repaired horseshoe seals"

BACKGROUND: CURRENT MWO DATA ENTRY



PHYSICAL PLANT
MAINTENANCE WORK ORDER

Date:

Requested by:

Building/Room:

Description of Needs:

Org. to be Charged:

Estimated Cost Amount:

Supervisor Approval: Date:

VP of Administration Approval: Date:

Work Completed by: Date:

Return completed form to Administrative Services
Rev 5/01

WORK ORDER FORMS

SPREADSHEETS

Date	Mach	Description	Issued By	Date Up	Maint Tech Assigned	Resolution
29-Jan-16	H15	St#14 tool detect INOP	JS	29-Nov-16	SA	Slug detector at station 14 not working. Would not recognize “Start” signal.
1-Jun-16	Mitsu FT	Brakes worn -Not stopping when in gear	AB	28-Jun-16	Steve A	Repaired
1-Jun-16	H8	St#7 rotator collet broken -wait for Bob B to show him how to remove	JS	8-Jun-16	John Smith	Machine went offline on 6/8 -Mark removed and instructed Bob B on removal/install process

Do “AI” to it! (…?)

Natural Language Processing (et al.) as Engineering Tools

TODAY'S TALK: TAKE-HOME

- NLP "Theory" Basics
  a. Data **models** and engineering **assumptions**
  b. NLP "**Tasks**" and **approaches**
  c. **Metrics** and **Evaluation**
- Contextualize NLP techniques, paradigms
  a. How NLP concepts interface with "Engineering Practice"
  b. Continuous interaction between experts (domain ←→ NLP)

TODAY'S TALK: STRUCTURE

Engineering Practice

- Goal & Approach
- Assumptions
- Measure & Evaluate
- Validate

"State the methods followed and why."

"State your assumptions."

"Apply adequate factors of safety."

"Always get a second opinion."

Hutcheson, M. L. (2003). *Software testing fundamentals: Methods and metrics*. John Wiley & Sons.

TODAY’S TALK: STRUCTURE

Engineering Practice

- Goal & Approach — *“State the methods followed and why.”*
- Assumptions — *“State your assumptions.”* — Start Here
- Measure & Evaluate — *“Apply adequate factors of safety.”*
- Validate — *“Always get a second opinion.”*

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ASSUMPTIONS

That turn “Natural Language” into something to “Process”

ASSUMPTIONS: RULE-BASED VS. NUMERICAL

Some very successful ways to “process” natural language involve **rules**.

Assume a language model based on known “logic”:

- Pattern Matching (e.g. regex), “coding”, etc.
- Clear definitions and transparent assumptions (iterate!)
- Can be **powerful** and **efficient**
- Can be **brittle** and **labor**-intensive

Newer techniques assume the text and its **statistical** properties **alone**

ASSUMPTIONS: THE CONTEXT SPECTRUM

- How do we turn text into "numbers"?
- Traditional techniques come in two "flavors"
  a. Bag-of-Words *(Global Frequency and Context)*
  b. Markov Model *(Local Sequence Probability)*
- Opposite answers to the question:

*"How much does **global** vs. **local** matter to you and/or this text?*

ASSUMPTION: GLOBAL FREQUENCY & CONTEXT

Basic Bag-of-Words

Words in similar ***contexts*** *<u>are</u>* ***similar****.*

- *Hydraulic leak at saw attachment*
- *Worn seal caused leak, replaced seal.*
- *Replaced saw, operator could have done this...*

	Hyd.	leak	saw	seal	rep.	...
Doc 1	1	1	1	0	0	...
Doc 2	0	1	0	2	1	...
Doc 3	0	0	1	0	0	...

- Remarkably Powerful
- Similarity is “vector directional”
  - Documents or Terms
  - → Cosine Similarity

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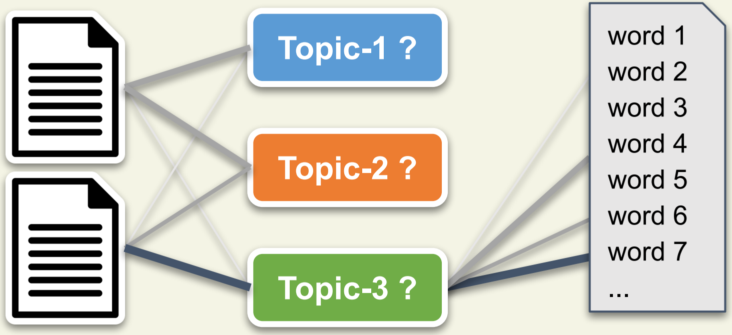
Modifications

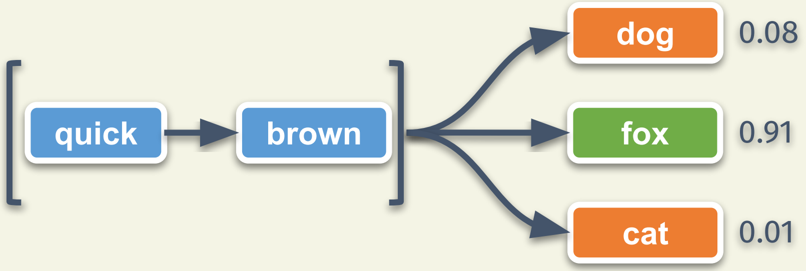
- Re-weighting schemes
  - Normalization, TF-IDF
  - Ties to informational entropy
- Dimension Reduction & **Topics**
  - Some "latent" set of topics:
    "Stuff we talk about" has less variety than "words we have"
  - Acronym soup
    PCA,SVD,LSA,NMF,LDA,TSNE,UMAP



ASSUMPTION: LOCAL SEQUENCE PROBABILITY

Markov Model

Next “states” (read: token/character) is conditionally dependent on the past:



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- High preference for observed sequences (precision)

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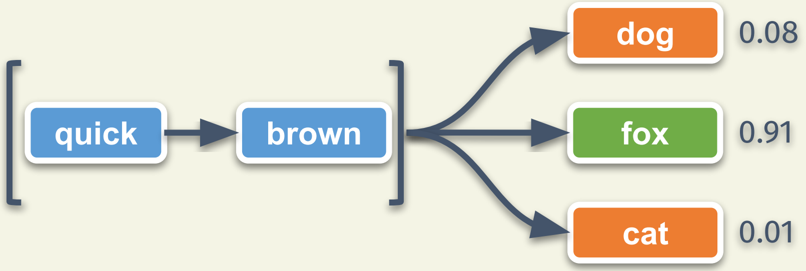

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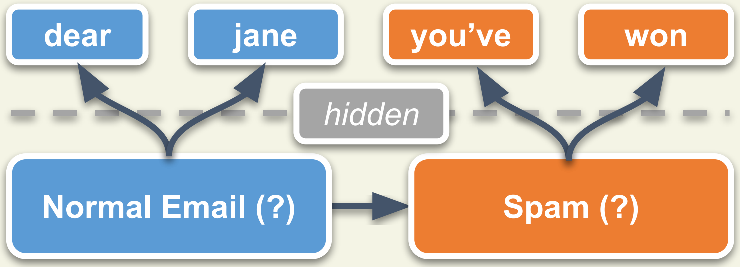
Hidden Markov Model

What we "observe" are emissions from a sequence of states we cannot observe.



- Used for last-gen. language models, bio-informatics, etc.
- Modular! See: GMMs, Bayes-nets…

ASSUMPTIONS: MODERN EMBEDDINGS

But... neural-nets?!

- We like the global context, but also want local sensitivity...
- Neural Nets can be "trained" to find a **vector space** model that **balances** both
  a. **Trained** is the operative term
  b. Packages/tools that let us "embed" text have **already trained** on a textual corpus
- You are assuming your text is "like" *that* text

*Otherwise these are an **approach**—and require proper design!*

ASSUMPTIONS: MORE ON "MODERN EMBEDDINGS"

- *Word2Vec (2013)* trains on a *word*-level
  - Continuous Bag-of-Words (**CBOW**): target word from local context
  - **Skip-Gram**: local context from target word
  - Maintains semantic linearity ("word algebra") — also see GloVe (2014)

lunch + night - day → dinner

better - good + bad → worse

wine + barley - grapes → beer

coffee - drink + snack = pastry

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- *BERT (2018)* is a *sub-word* model...**context** (sentence) dependent!
  - Can capture separate semantic meaning (homophones) and out-of-vocab.
  - State-of-the-art in 2019; used for your Google searches.

GOALS & APPROACH

NLP Tasks and “The Pipeline”

GOALS & APPROACHES: OVERVIEW

- Typical NLP Tasks
  (and their image-processing relatives)
  a. Document Grouping, Classification
  b. Keyword Extraction, Multi-Label Classification
  c. Named Entity Recognition and Parts-of-Speech
- The NLP "Pipeline"
  a. Preprocessing
  b. Analyses

GOAL: DOCUMENT TYPING

- Clustering (Unsupervised)
  - Detect “natural groupings” for analysts to parse
  - Also: interpreting topic models
  - May or may not be relevant, but a useful tool

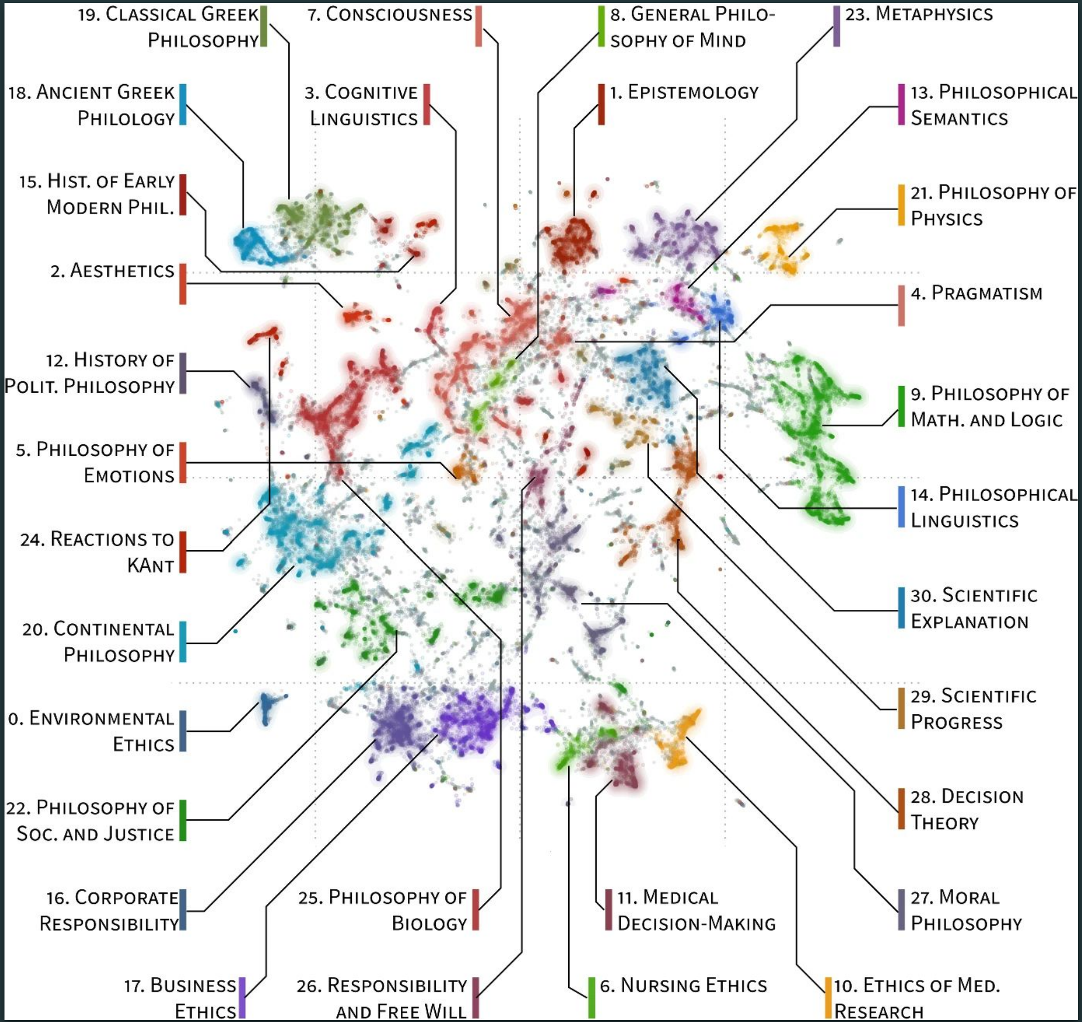
The Structure of Recent Philosophy

Noichl, M. Modeling the structure of recent philosophy. *Synthese* **198**, 5089–5100 (2021). https://doi.org/10.1007/s11229-019-02390-8

Each "dot" is a paper.

- Embed to 2-dimensions (UMAP)
- Clustering (HDBScan)
- Interpret, synthesize (hard)

Fully interactive online:
https://homepage.univie.ac.at/maximilian.noichl/full/zoom_final/index.html



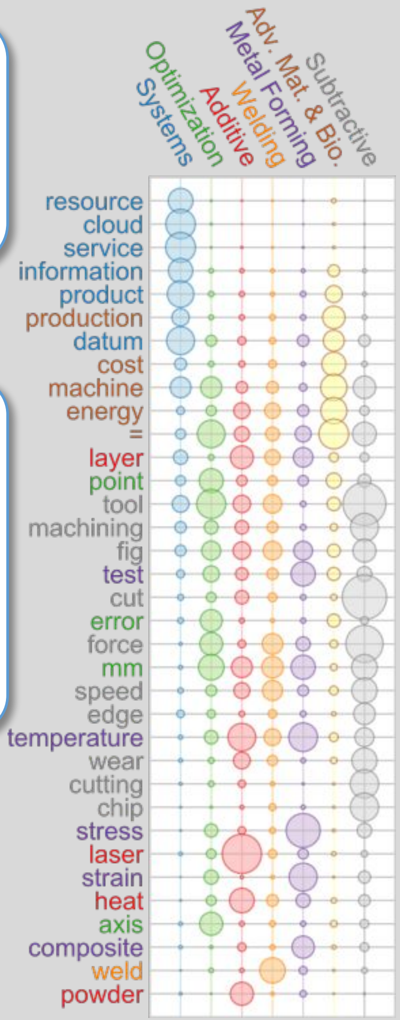
MSEC: A Quantitative Retrospective

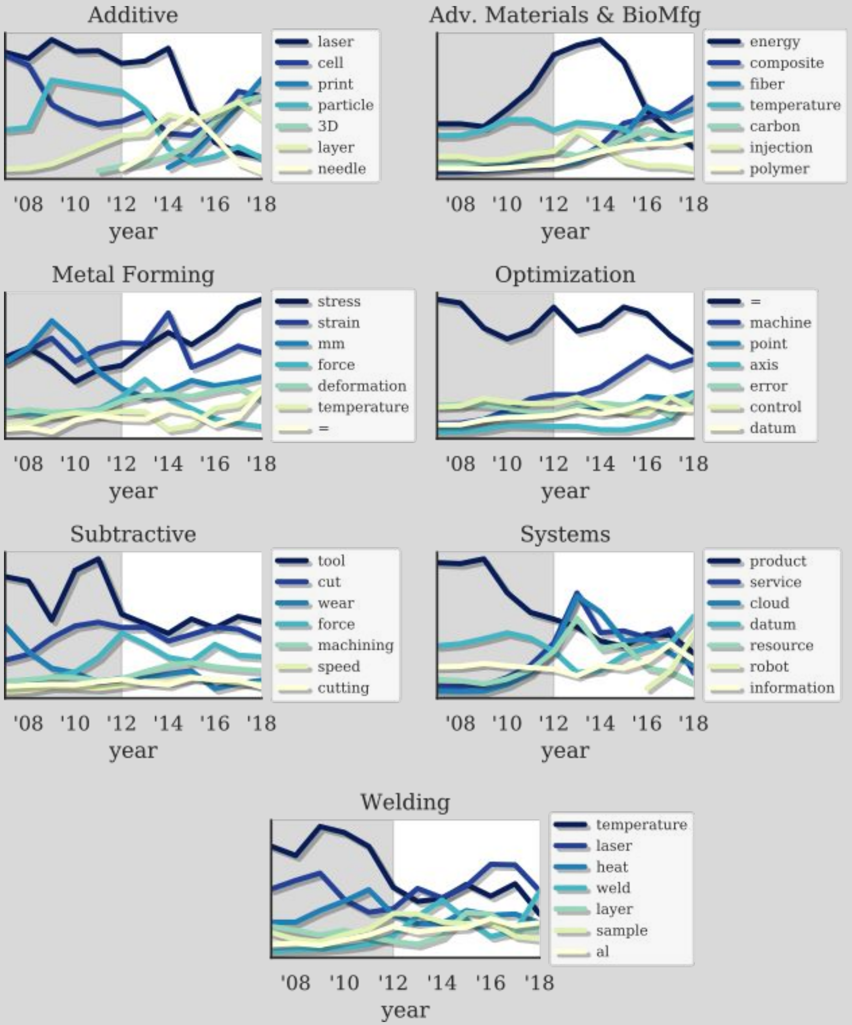
Sexton, T, Brundage, MP, Dima, A, & Sharp, M. "MSEC: A Quantitative Retrospective." September 2020
https://doi.org/10.1115/MSEC2020-8440

Topic Models as an approach to typing:

- Useful understanding
- LDA for static
- Dynamic LDA over time

We had to name the topics.





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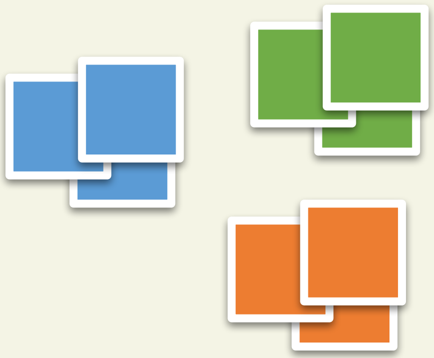
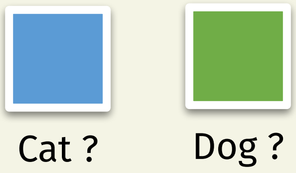


- Classification (Supervised)
  - Labels required: 1 per category (mutually exclusive)
  - Can be useful for recommendations: “relevant vs. not”
  - Images: “*is this a stoplight?*” or “*which animal?*”, etc.



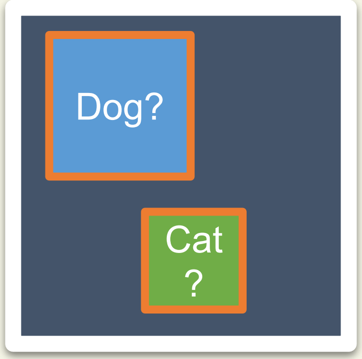
GOAL: DOCUMENT KEYWORDS

- Keyword Extraction (Unsupervised)
  - Use statistical properties to find “important terms”
  - Also see: text summarization
  - TF-IDF (sum), TextRank (graph-based), YAKE, +more

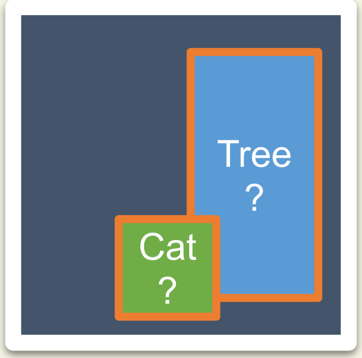
- Multi-Label Classification (Supervised)
  - Labels required: **multiple**-per-document (multiset)
  - Several ways to train, can use domain-knowledge
  - **Harder** problem, but maybe easier to **make** training data...
  - Images: “*What animals are present?*”

GOAL: ENTITY RECOGNITION

- Named Entity Recognition
  - Find **text spans** that contain **keywords**, and **annotate** them
  - Predetermined vocabulary/taxonomy (usually 2-levels)
  - E.g. “I went to New York [LOC]” or “They owe me $25 [CURR]”
  - Images: *“highlight and label the animals…”*



- Parts-of-Speech
  - Automatic determination of **grammar** information
  - SVO triples, dependency parsing, etc.
  - Can be used to “mine” **knowledge graphs**
  - Domain/language-dependent… hard with technical text!



GOALS: OTHERS WORTH MENTIONING

Wide variety of other tasks:

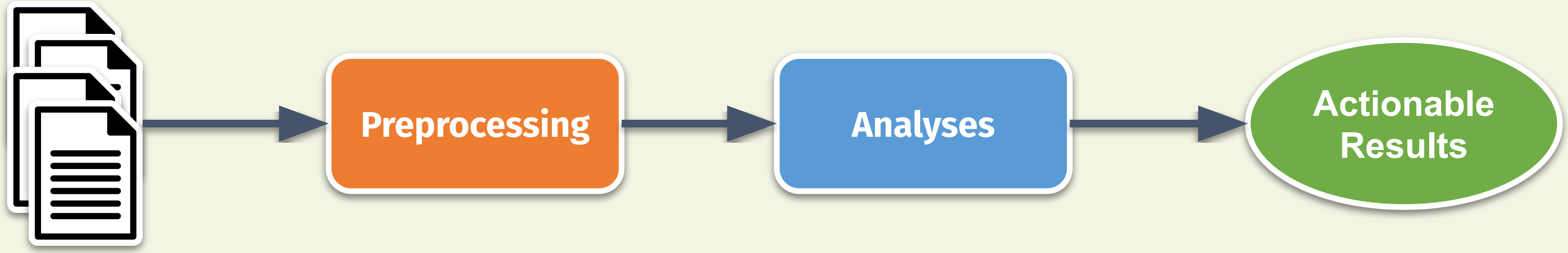
- Sentiment Analysis
- Seq2Seq & Machine Translation
- Reading complexity and writing quality, inclusivity
- Question Answering
- Text Synthesis

What does it take to get to this point?

PROCESS: "THE PIPELINE"

In theory, the NLP Pipeline is a

- Sequential progression, that
- Provides usable insight



Impossible to outline the number of variations on this "theme"... Here's:

- A common sequence — a *day-in-the-life* of your analyst.
- Benefits and drawbacks of each step

PROCESS: TEXT PREPROCESSING

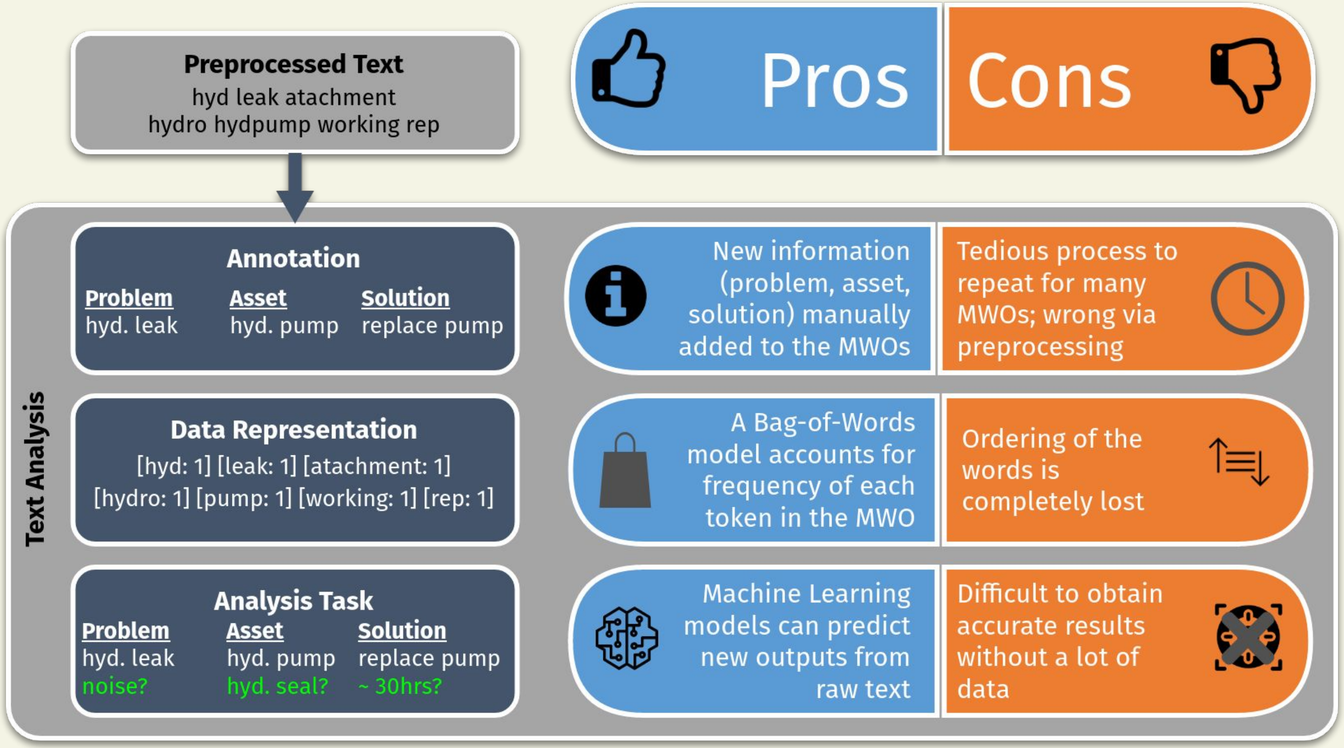
Raw Text
Hyd leak at saw atachment Hydromat Saw 012, hydpump not working, rep with new HS012

Preprocessing

	Pros	Cons
Tokenizer {hyd}{leak}{at}{saw}{atachment}{hydromat}{012}{,}{hydpump}{not}{working}{rep}{with}{new}{hs012}	Each word successfully broken into an individual token	Hydpump not tokenized correctly
Stop Word Remover {hyd}{leak}{atachment}{hydromat}{012}{,}{hydpump}{working}{rep}{hs012}	All stop words removed	NOT, SAW, NEW have important meaning and were removed
Cleaner {hyd}{leak}{atachment}{hydromat}{hydpump}{working}{rep}	Punctuation removed	HS012 is an asset number; still removed
Stemmer hyd, hydraulic, hydromat, hyrdaulic → hyd, hydraul, hydro, hyda	Hydromat correctly linked to hydro	Hyd, Hydraulic, Hyrdaulic not linked

Technical language processing: Unlocking maintenance knowledge. Brundage, M. P., Sexton, T., Hodkiewicz, M., Dima, A., & Lukens, S. (2021). *Manufacturing Letters*, *27*, 42-46.
Image adapted from original.

PROCESS: TEXT ANALYSES



Technical language processing: Unlocking maintenance knowledge. Brundage, M. P., Sexton, T., Hodkiewicz, M., Dima, A., & Lukens, S. (2021). *Manufacturing Letters*, *27*, 42-46.
Image adapted from original.

MEASURE & EVALUATE

Importance of metrics and knowing what gets evaluated

MEASURE & EVALUATE: OVERVIEW

Key skill of the analyst or engineer is knowing how to **translate:**

Qualitative *needs and constraints* → ***Quantitative*** *metrics and evaluations*

- What do I want to measure?
  - Do **my assumptions** conflict with the measurement?
  - Do the **metric's assumptions** conflict with my goal/process?
  - Will **multiple metrics** provide a broader insight? (yes)
- What constitutes progress toward, or success in, my goal?
  - Have I encoded my (stakeholder) expectations (preferences) sufficiently?
  - Do I have parameters to tune (continuously and/or iteratively)?

Most important: have I **transparently documented** my decisions for **iteration**?

MEASURE

What do I need to measure? Have I “done my homework”?

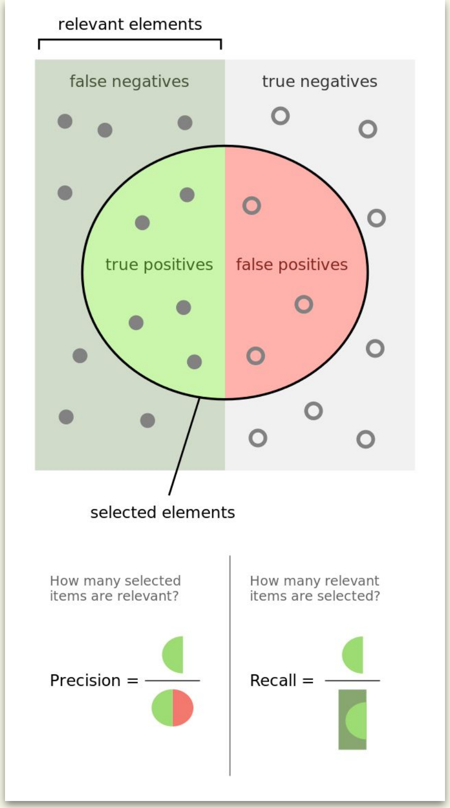
- Similarity or Distance
  - Discrete options, spellings: *Levenstein, Hamming, SymSpell, Jaccard*
  - Vector/Geometry: *Euclidean, Mahalanobis, Minkowski*
  - Distributions: *Kullback-Leibler, Earth-mover/Wasserstein, Cross-Entropy*
- Quality
  - Annotation coverage, label/class imbalance (rare-event?)
  - “Usefulness”: *topic perplexity, (B/A) Information Criterion*
  - Inter-rater agreement: *Fleiss’* κ, *Kendall’s* τ, *graph-based?*
- Importance
  - Information content: *Shannon Entropy, log-odds, lift, sum-TFIDF*
  - Centrality: *degree, betweenness, spectral (e.g. TextRank),*

EVALUATE: PRECISION & RECALL

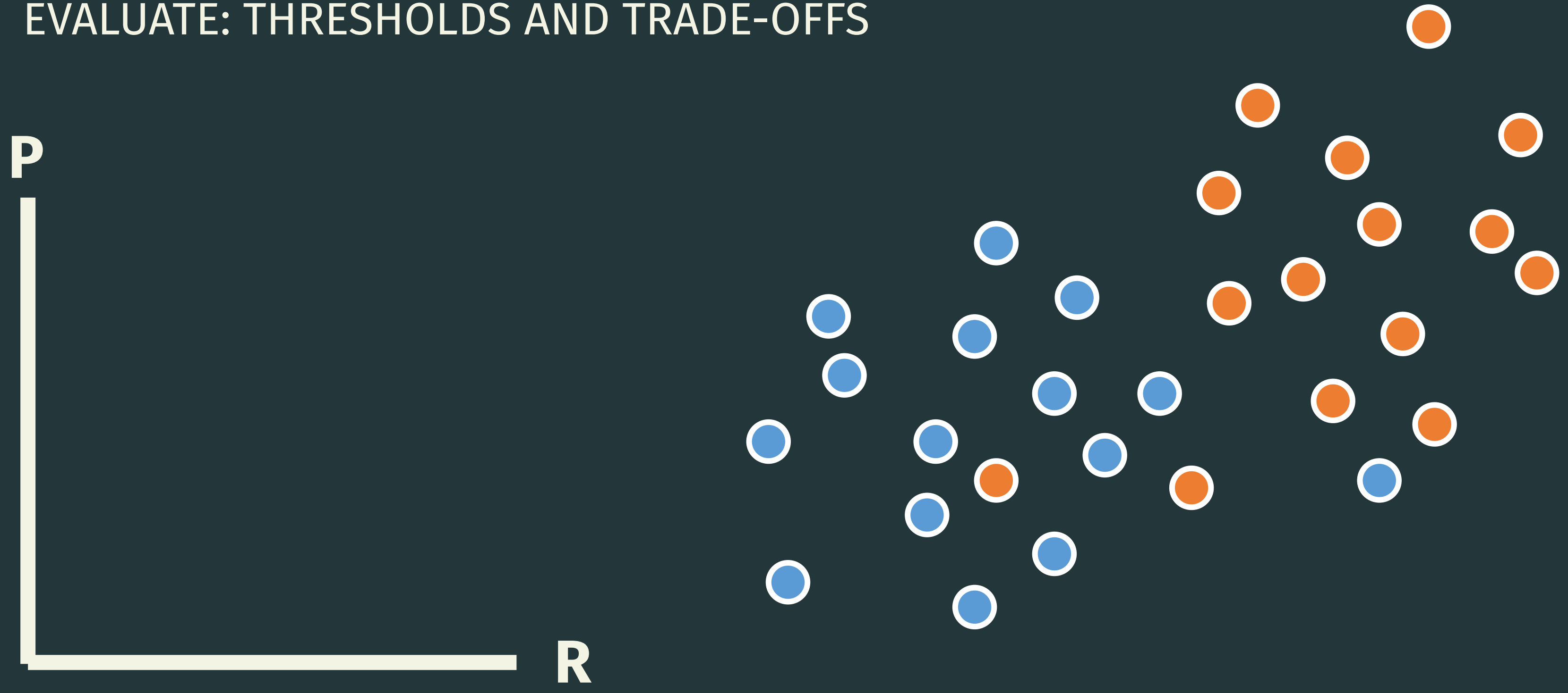
NLP often involves *multilabel* or *imbalanced* classification.

→ Accuracy is **unfair** or **overly optimistic**

- Precision
  - Also *Positive Predictive Value (PPV):* [TP/(TP+FP)]
  - “Of things **predicted** X, how many **are** X?”
- Recall
  - Also *True Positive Rate* or *Sensitivity:* [TP/(TP+FN)]
  - “Of the things that **are** X, how many were **predicted** X?”
- F-Score
  - Harmonic mean of Precision & Recall:
  - Explicitly combines our preferences for the two
  - Parameter **β** (usually 1) : assign **β**-times more importance to Recall than precision.



EVALUATE: THRESHOLDS AND TRADE-OFFS



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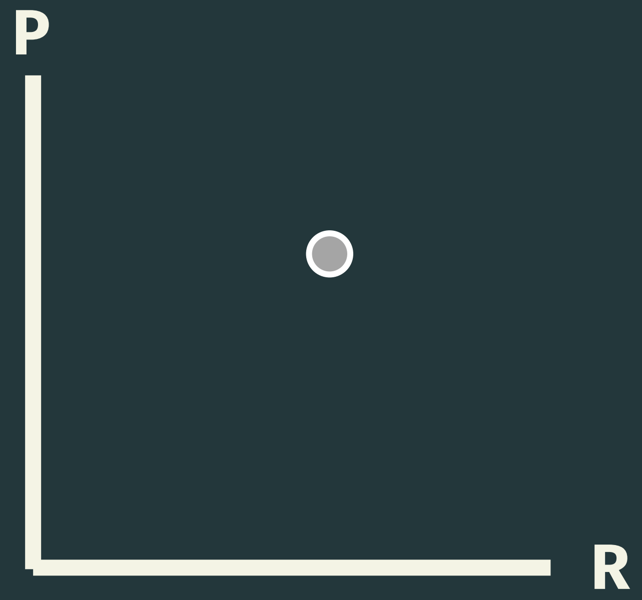

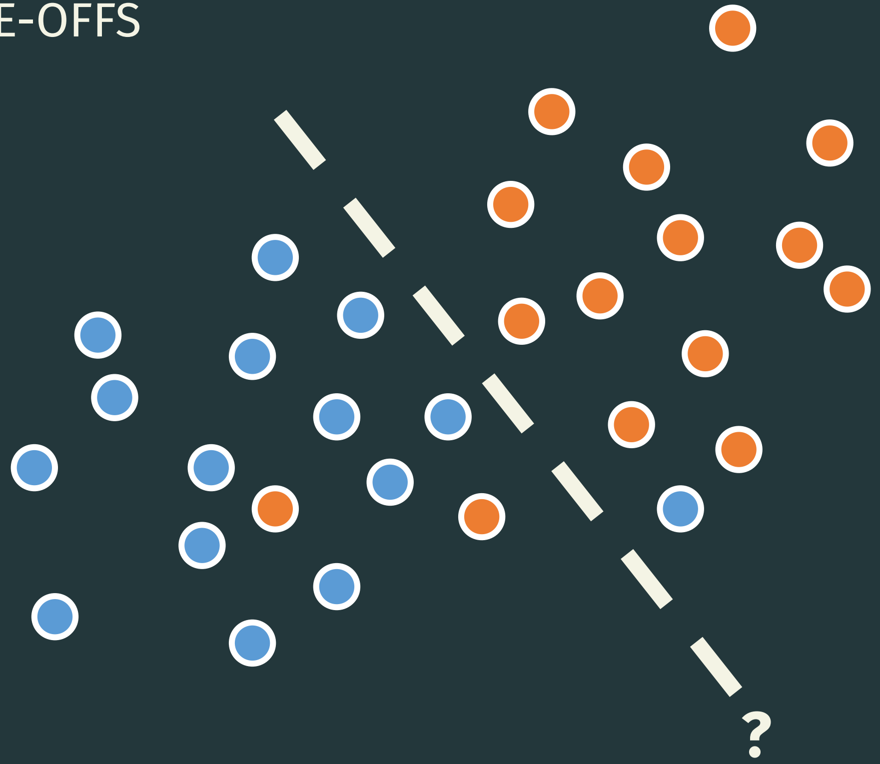

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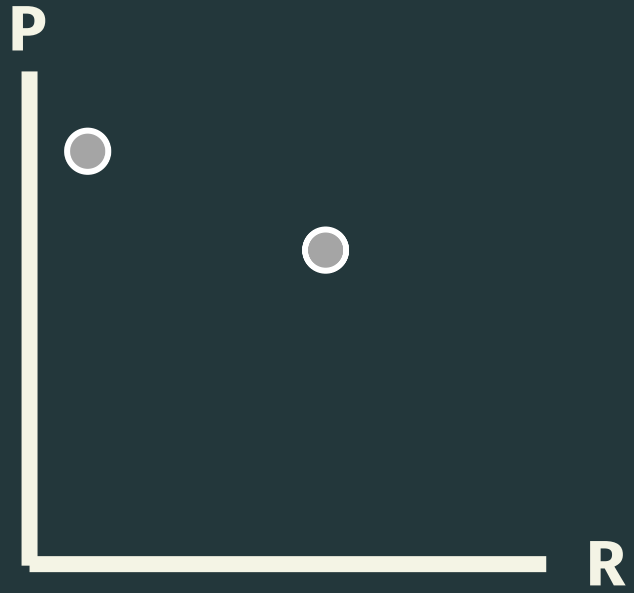

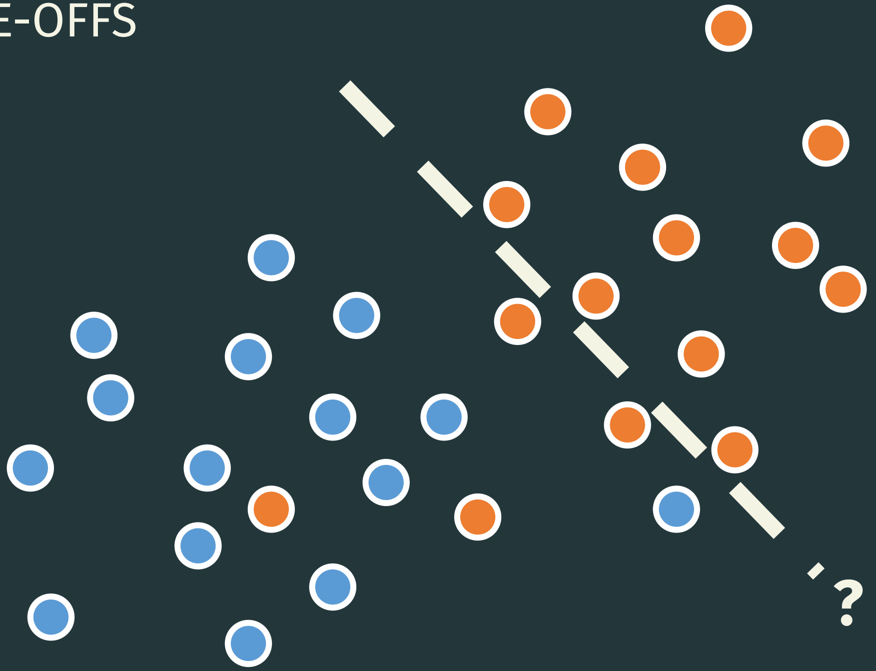

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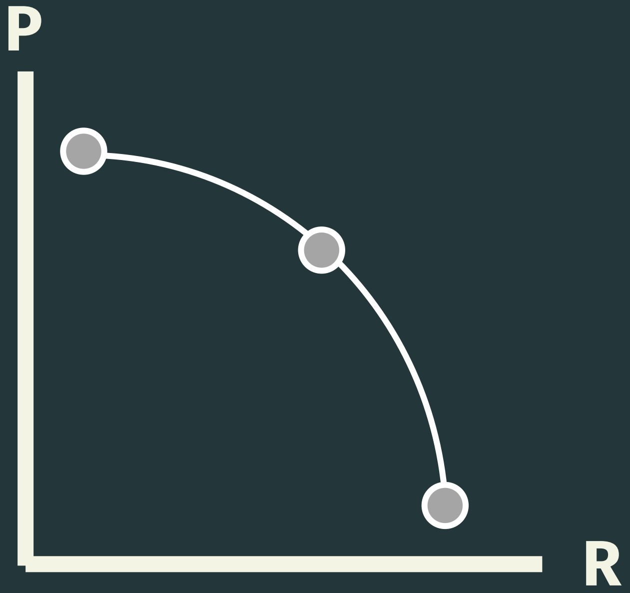

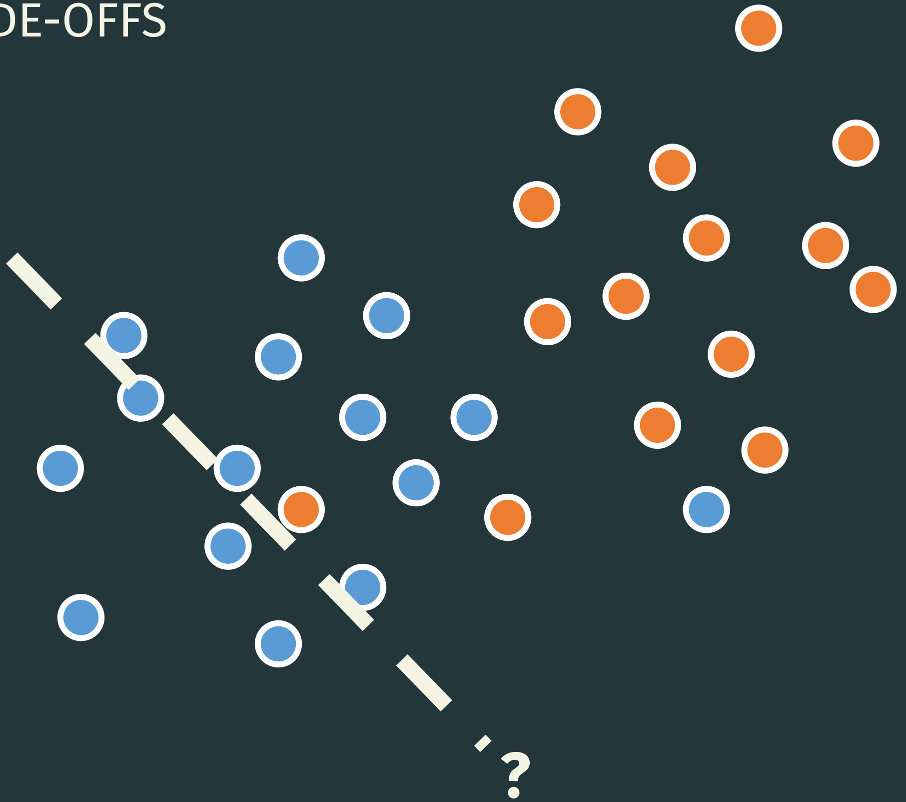

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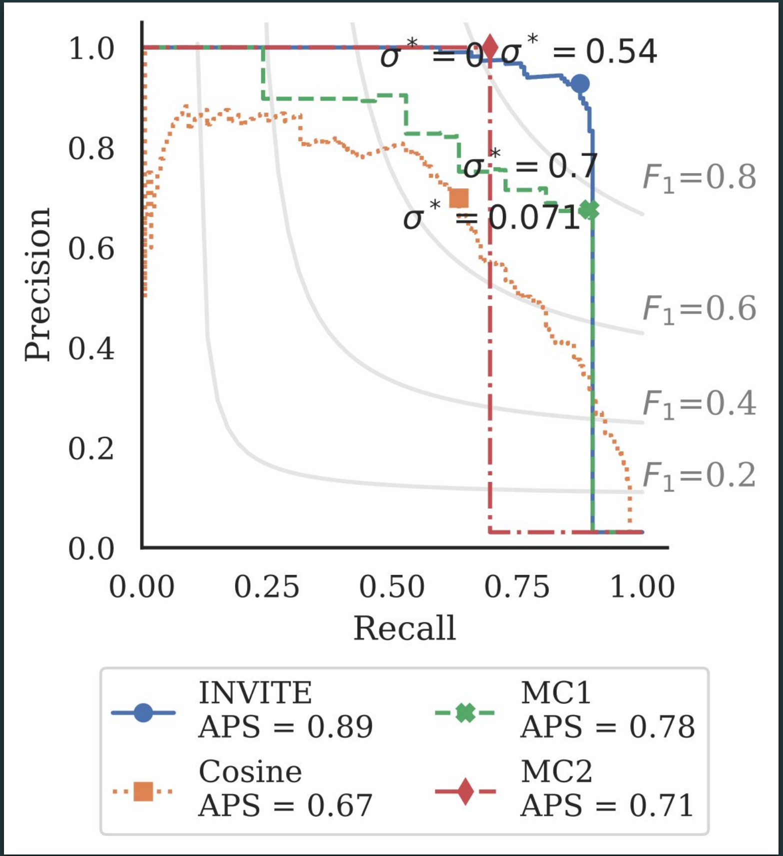
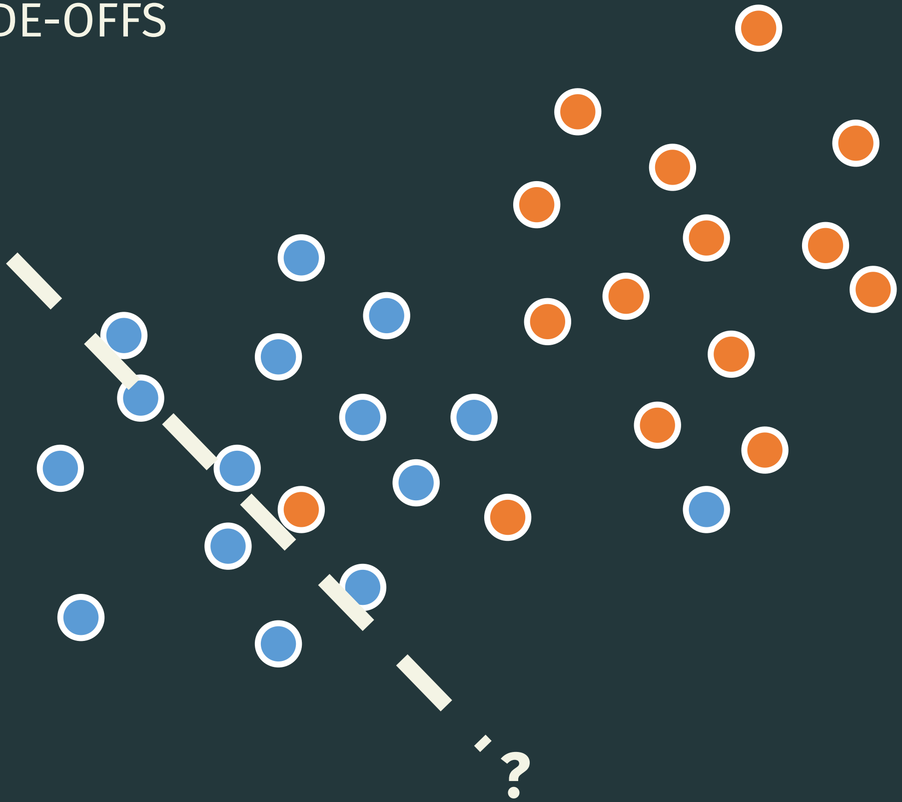




Sexton, T., and Fuge, M. (January 13, 2020). "Organizing Tagged Knowledge: Similarity Measures and Semantic Fluency in Structure Mining." ASME. *J. Mech. Des.* March 2020; 142(3): 031111. https://doi.org/10.1115/1.4045686

EVALUATE: SUMMARY

Do your **homework**

If there's something you want to measure, a metric may exist.

Metrics **evaluate**

Use fundamentals to design metrics that assess what matters.

Metrics **communicate**

Confusion is never the answer; strive for mutual understanding.

Remember that NLP is working on data *for humans, by humans.*

*Be **transparent** and **reproducible**.*

VALIDATION

The “open problem” of human-in-the-loop, domain-specific NLP

VALIDATION: PROBLEMS

So far we have glossed over some very common problems:

- Interpreting topic models can be fraught [1]
- Out-of-the-box tools are pre-trained on *very* different text
- There is not enough data to train custom models
- Too hard to hand-annotate the data we have
- No existing standard annotation to apply, no ontology we agree on
- Events of interest are far too rare (unclear if over-sampling applies)
- ...

In most Engineering Design and Reliability tasks, we *validate:*

Sanity checks, second opinions, processes for oversight and collaboration

[1] *Chang, Jonathan, et al.*
"Reading tea leaves: How humans interpret topic models."
Neural information processing systems. Vol. 22. 2009.

VALIDATION: RE-ASSESSING “THE PIPELINE”

Reality is never as clean as “The Pipeline”.

> *“In practice, the line between input and output are not well defined. An analyst might use intermediary tasks and representations to enrich annotations and cascade into further tasks. A holistic approach to improving one component will inevitably improve the others; a stolid adherence to a given pipeline can prevent progress all-around.*
>
> *[...]*
>
> *By lowering barriers to entry for text analysis through the development of efficiency-boosting tools and a more human-centered annotation approach, engineers have a unique opportunity to simultaneously learn from other domains and improve on their processes. A new approach is needed to adapt NLP methods to industry use cases in a scalable and reproducible way.*[1]

→ View NLP as a socio-technical system rather than as an algorithmic pipeline.

[1]Brundage, Michael P., et al.
"Technical language processing: Unlocking maintenance knowledge."
Manufacturing Letters 27 (2020): 42-46.

VALIDATION: TECHNICAL LANGUAGE PROCESSING

Enter ***Technical Language Processing***

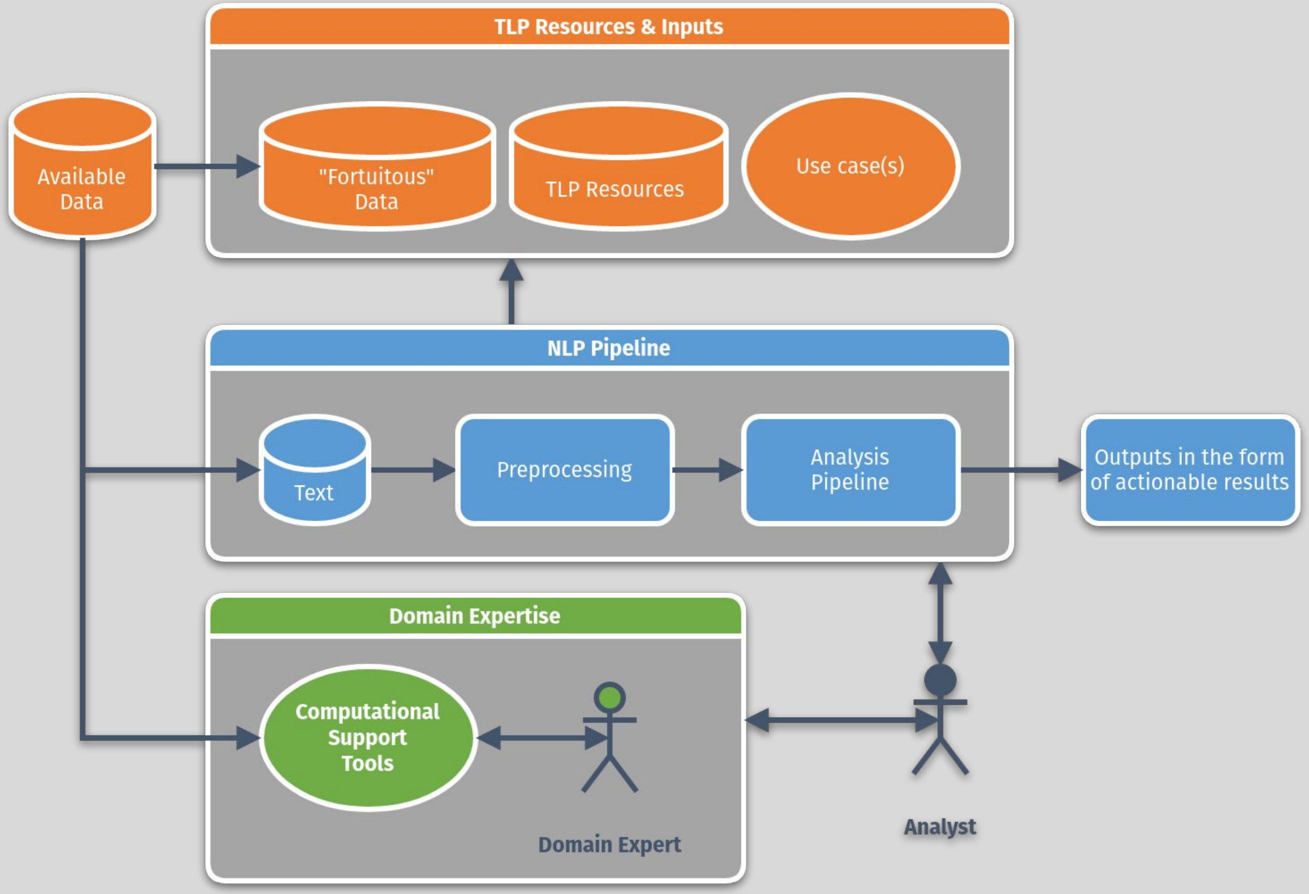
- NLP Techniques do not *always* adapt well to engineering text

- Current NLP solutions need to be adapted ***correctly*** for use in technical domains

- TLP is a methodology to tailor NLP solutions to engineering text and industry use cases in a scalable and reproducible way

Adapting Natural Language Processing for Technical Text
Dima, Alden, et al.
Applied AI Letters: e33.
Image adapted from original

- How the TLP approach to meaning and generalization differs from NLP
- How data quantity and quality can be addressed
- Potential risks of *not* adapting NLP



VALIDATION: GET INVOLVED

Plan for Distributed Collaboration in the TLP CoI

I. GitHub Organization (just started): **TLP-CoI**
   A. Documentation - best practices for TLP, theory, etc
   B. Networking - curated list for state-of-the-practice: awesome-tlp
   C. Collaboration - base or forks for open tool repositories

II. Events:
   A. Past Workshop (slides):
   B. TLP-COI Slack Workspace - QR code →
   C. Other options? Webinars? Let us know!

THANK YOU

Thurston Sexton

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U.S. Department of Commerce