# **CS 337**: Tips + Tricks for Project 1

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*Credit to past TA Victor Bursztyn – some examples/ideas taken from his version of this deck!*

# Outline

1. Framing the tasks
    a. How-to: searching strings → candidate answers
    b. How-to: syntactic parsing and entity recognition
2. Pre-processing the dataset
    a. How-to’s: cleaning text in individual tweets
    b. How-to: language detection
3. Tweet-specific features
    a. Hashtags and usernames
    b. Re-tweets and quote tweets
    c. Tweet timestamps

# **Framing**: evaluation setting

*Core challenge of Project 1*: how can we build a robust information extraction system that can generalize to unseen, real-world data?

- You'll build-test-iterate using tweets from the 2013 Golden Globes
- But, you'll be **graded on a hidden test set of tweets from other award shows**
  - Could be other years of Golden Globes, other entertainment-related award shows
  - Structure and general domain of data won't change, though

Task components: faithfully reconstruct information about these categories:

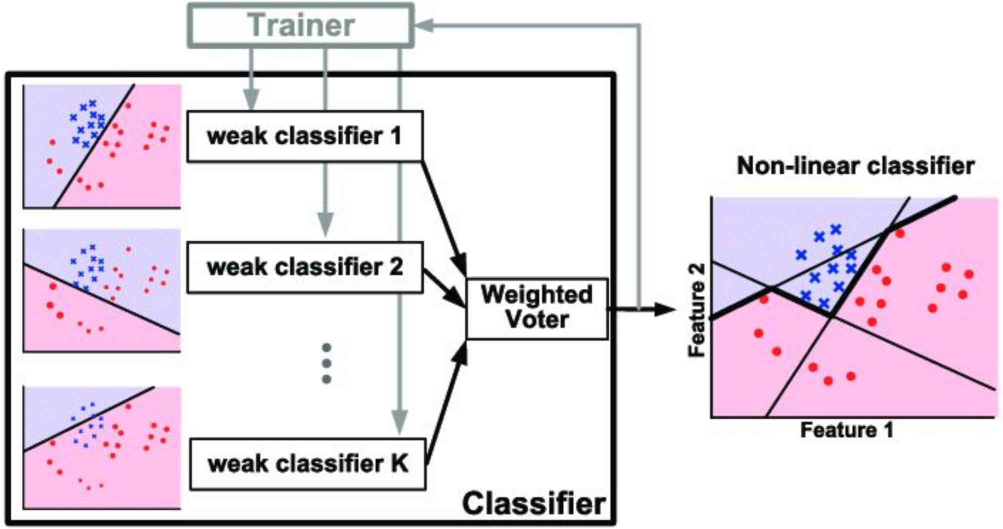
*host(s); award names;*
*presenters for each award; nominees for each award; and winner(s) of each award*

# **Framing**: challenges across project tasks

- **Dataset noise**
    - Typos, internet slang and syntax, tweets in different languages, diverse formats for quote tweets/retweets,  …
- **Task category complexities** – e.g., for award names:
    - A single “real” award is often referred to with various shortened forms
    - Less interest in some awards results in disproportionately fewer tweets
    - Popularity of “unofficial awards” (e.g. best dressed) makes ^ problematic
- **Evaluation setting**: useful features in training data have no guarantee of being useful in evaluation data

# **Framing**: ensembling weak rules → strong parser

1. Curate a diverse set of weak parsing rules: each one should extract *decent* predictions related to one of the award categories.
2. Using the sets of weak predictions, merge related answers and return a re-scored set of candidate answers.



(source)

# **Example**: weak rules for award names

- One approach – searching for specific words/expressions:
  - Award names: might include the words “best” or “award”
  - Use the “script” of an award show to brainstorm:
    - Pre-winner: “nominees for X”, “is nominated for X”, “I bet X goes to”, …
    - Reporting winner: “Y wins X”, “X goes to Y”, “Y takes home X”, …
    - Post-winner: “Y celebrates X win”, “X should have gone to”, …
    - …

# **Example**: matches for “[entity] wins [award]”

*RT @HuffingtonPost:* Anne Hathaway wins best supporting actress *#GoldenGlobes http://t.co/fXsNg1h*

- How do we know where [entity] and [award] begin and end?

# **Example**: matches for “[entity] wins [award]”

*RT @HuffingtonPost:* Anne Hathaway wins best supporting actress *#GoldenGlobes http://t.co/fXsNg1h*

- How do we know where [entity] and [award] begin and end?
- One option: collect all possible candidate answer phrases
  - best
  - best supporting
  - best supporting actress
  - best supporting actress #GoldenGlobes
  - best supporting actress #GoldenGlobes http://t.co/fXsNg1h

# **How-to**: default methods for string search

```
tweet = “RT @HuffingtonPost: Anne Hathaway wins best supporting actress
        #GoldenGlobes http://t.co/fXsNg1h”
```

**Splitting on “ wins ” via python built-ins**

```
win_split = tweet.split(“ wins ”)
>> [
    'RT @HuffingtonPost: Anne Hathaway',
    'best supporting actress #GoldenGlobes http://t.co/fXsNg1h'
   ]
```

**Splitting on “ ”**

```
left_side_words = win_split[0].split()
>> ['RT', '@HuffingtonPost:', 'Anne', 'Hathaway']
```

# **How-to**: getting candidate answer strings

```
tweet = “RT @HuffingtonPost: Anne Hathaway wins best supporting actress
        #GoldenGlobes http://t.co/fXsNg1h”
```

**Right side of rule: collect candidate answers**

```
if “ wins “ in tweet:  # assuming only one instance of “ wins “ exists...
    win_split = tweet.split(“ wins ”)
    words, candidate_answers = win_split[1].split(), []
    for ix in range(len(words)):
        candidates.append(“ “.join(words[:ix + 1]))

>> ['best', 'best supporting', 'best supporting actress',
    'best supporting actress #GoldenGlobes',
    'best supporting actress #GoldenGlobes http://t.co/fXsNg1h']
```

# **How-to**: getting candidate answer strings

```
tweet = “RT @HuffingtonPost: Anne Hathaway wins best supporting actress
        #GoldenGlobes http://t.co/fXsNg1h”
```

**Left side of rule: collect candidate answers**

```
if “ wins “ in tweet:  # assuming only one instance of “ wins “ exists...
    win_split = tweet.split(“ wins ”)
    words, candidate_answers = win_split[0].split(), []
    for ix in range(len(words)):
        candidates.append(“ “.join(words[ix:]))
    candidates = candidates[::-1]  # reverse order of results

>> ['Hathaway', 'Anne Hathaway', '@HuffingtonPost: Anne Hathaway',
    'RT @HuffingtonPost: Anne Hathaway']
```

# **How-to**: regex methods for string search

```
tweet = “RT @HuffingtonPost: Anne Hathaway WINS best supporting actress
        #GoldenGlobes http://t.co/fXsNg1h”
```

**Flexible splitting using regex:**

```
re.findall(r"(.+) (wins|Wins|WINS) (.+)", tweet)

>> [('RT @HuffingtonPost: Anne Hathaway',
     'WINS',
     'best supporting actress #GoldenGlobes http://t.co/fXsNg1h'
   )]
```

# **How-to**: regex methods for string search

```
tweet = “RT @HuffingtonPost: Anne Hathaway receives best supporting actress
        #GoldenGlobes http://t.co/fXsNg1h”
```

**Flexible splitting using regex:**

```
re.findall(r"(.+) (wins|Wins|WINS|receives|received|gets) (.+)", tweet)

>> [('RT @HuffingtonPost: Anne Hathaway',
     'receives',
     'best supporting actress #GoldenGlobes http://t.co/fXsNg1h'
   )]
```

# **Example**: matches for “[entity] wins [award]”

*RT @HuffingtonPost:* Anne Hathaway wins best supporting actress *#GoldenGlobes http://t.co/fXsNg1h*

- How do we know where [entity] and [award] begin and end?
- Returning to our possible candidate answers…
  - best
  - best supporting
  - best supporting actress
  - best supporting actress #GoldenGlobes
  - best supporting actress #GoldenGlobes http://t.co/fXsNg1h

# **Example**: matches for “[entity] wins [award]”

*RT @HuffingtonPost:* Anne Hathaway wins best supporting actress *#GoldenGlobes http://t.co/fXsNg1h*

- How do we know where [entity] and [award] begin and end?
- Simple filters can improve quality of candidates
  - Award names aren’t just single-word superlatives/adjectives
  - best supporting
  - best supporting actress
  - Award names aren’t mixtures of text and hashtags
  - Award names don’t include links

# **Example**: matches for “[entity] wins [award]”

*RT @HuffingtonPost:* Anne Hathaway wins best supporting actress *#GoldenGlobes http://t.co/fXsNg1h*

- How do we know where [entity] and [award] begin and end?
- Useful to explore the diversity of “good” matches:
  - *Les Miserables wins Best Motion Picture, Comedy or Musical.*
  - *#LesMiserables wins for Best Comedy/Musical*
  - *Les Miserables wins Best Comedy or Musical*
  - *Les Mis wins comedy/musical award.*
  - *Les miserablés wins best motion picture!!*
- … 4 distinct [entity] spans; 5 distinct [award] spans …

# **Example**: matches for “[entity] wins [award]”

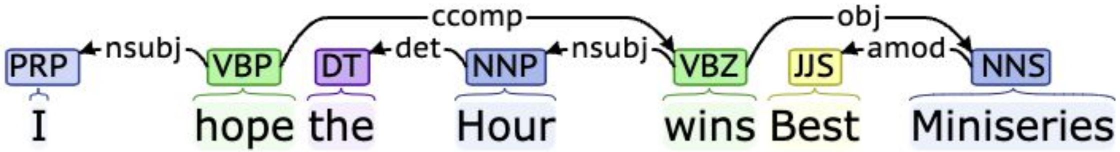
*RT @HuffingtonPost:* Anne Hathaway wins best supporting actress *#GoldenGlobes http://t.co/fXsNg1h*

- How do we know where [entity] and [award] begin and end?
- Useful to explore the diversity of “bad”/“tricky” matches:
  - *I hope the Hour wins Best Miniseries*
  - *Maggie Smith, the Dowager Countess, wins Best Supporting Actress*
  - *Adele's Skyfall wins best original song*
- … Motivates a broader (*but quick*) aside on syntactic parsing

# **How-to**: motivating syntax (useful reference)

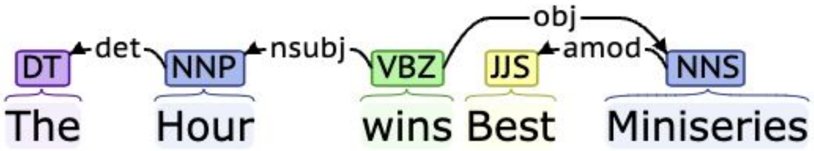
“I hope the Hour wins Best Miniseries”

- **root** of syntax tree is “**hope**”; “**wins**” is a **clausal complement** of “**hope**”



“The Hour wins Best Miniseries”

- New **root** of syntax tree is “**wins**”



# **How-to**: syntactic parsing – dependency trees

**Parsing dependency trees** (spacy link)**:**

```
import spacy

spacy_model = spacy.load(“en_core_web_sm”)
spacy_output = spacy_model(input_sentence)
for token in spacy_output:
      print(
            token.text,
            token.dep_,
            token.head.text,
            token.head.pos_,
            [child for child in token.children]
      )
```

**I hope the Hour wins Best Miniseries**

**Dependency parse:**

- I | nsubj | hope | VERB | []
- hope | **ROOT** | hope | VERB | [I, **wins**]
- the | det | Hour | PROPN | []
- Hour | nsubj | wins | VERB | [the]
- wins | **ccomp** | hope | VERB | [Hour, Miniseries]
- Best | compound | Miniseries | PROPN | []
- Miniseries | dobj | wins | VERB | [Best]

# **How-to**: syntactic parsing – noun chunks

## Noun chunks:

```
import spacy

spacy_model = spacy.load(“en_core_web_sm”)
spacy_output = spacy_model(input_sentence)
for chunk in spacy_output.noun_chunks:
      print([chunk.text, chunk.root.head.text])
```

## Results on the right:

- Use caution: Model fails with @/# changes and less grammatical syntax
- Extra motivation to do good tweet-aware preprocessing of data

| Input sentence | Child noun chunks of “won” |
|---|---|
| Ben Affleck won best director! | “Ben Affleck”, “best director” |
| I just heard that Ben Affleck won best director and he was beyond grateful! | “Ben Affleck”, “best director” |
| @BenAffleck won #BestDirector! | “BestDirector” |
| YAY Ben Affleck won best director omg! | “YAY Ben Affleck”, “best director omg” |

# **How-to**: entity recognition

**Entity recognition with SpaCy:**

```
import spacy

spacy_model = spacy.load(“en_core_web_sm”)
spacy_output = spacy_model(input_sentence)
for entity in spacy_output.ents:
     print([entity.text, entity.label_])
```

**Results on the right:**

- Same issues with @/#s
- Caution: the entity label isn’t always correct! Lots of noise here

| Input sentence | Entity output |
|---|---|
| Ben Affleck won best director! | `[Ben Affleck, PERSON]` |
| I just heard that Ben Affleck won best director and he was beyond grateful! | `[Ben Affleck, PERSON]` |
| @BenAffleck won #BestDirector! | `[#, CARDINAL]` |
| YAY Ben Affleck won best director omg! | `[YAY Ben Affleck, PERSON]` |

# **Framing**: choosing the best candidate answers

```
["Les Miserables", "Les Miserables", "#LesMiserables", "Les Mis", "Les miserablés", ... ]
[“Best Motion Picture, Comedy or Musical”, “Best Comedy/Musical”, “Best Comedy or Musical”]
```

- **Merging answers:**
  - “Best Comedy/Musical” == “Best Comedy or Musical”
  - “best motion picture - comedy or musical” != “best motion picture - drama”
- **Ranking final answers** – should we prefer…
  - “Best Motion Picture, Comedy or Musical”?
  - “Best Comedy/Musical”?
  - …

# **Framing**: choosing the best candidate answers

```
["Les Miserables", "Les Miserables", "#LesMiserables", "Les Mis", "Les miserablés", ... ]
[“Best Motion Picture, Comedy or Musical”, “Best Comedy/Musical”, “Best Comedy or Musical”]
```

- **Merging answers:**
  - Edit distance – “Miserablés” vs “Miserables”
  - Co-occurring context – “Anne Hathaway” often mentioned w/ "Les Miserables"
  - Component words – ignore order/punctuation → [“best”, “comedy”, “musical”]
  - External knowledge – querying imdb for “Les Mis” vs. “Les Miserables”
  - Tweet timestamps – (in later slides)
  - …

# **Framing**: choosing the best candidate answers

```
["Les Miserables", "Les Miserables", "#LesMiserables", "Les Mis", "Les miserablés", ... ]
[“Best Motion Picture, Comedy or Musical”, “Best Comedy/Musical”, “Best Comedy or Musical”]
```

- **Ranking final answers:** can use frequency of answer candidates, **but beware!**
  - Example case: failure modes when choosing final list of award categories
    - Award name categories are often referred to by shortened names
    - Unofficial awards like “Best Dressed” are extremely common
    - Some awards are tweeted about less, e.g. best foreign film
- **Contextual metrics for confidence are extremely useful!** Examples:
  - Some parsing patterns might be more accurate – upweight those!
  - What are signs that a tweet is reputable? An account?

# Pre-processing the dataset

# **Pre-processing**: misc. text processing tips (1)

- The data has some artifacts that were introduced when the tweets were initially scraped from Twitter
- Example:

  “‘Kerry Washington in Miu Miu **&amp;** Prada!!!! OH.......EM.......GEE!!!!!!!!!! **&lt;**3 #GoldenGlobes #redcarpet’”

- I universally recommend doing this!
- We can use the ftfy library to fix these:

```
pip install ftfy
```

**Code**:

```
from ftfy import fix_text

fixed_text = fix_text(original_text)
```

**Output**:

“Kerry Washington in Miu Miu **&** Prada!!!! OH.......EM.......GEE!!!!!!!!!! **<**3 #GoldenGlobes #redcarpet”

# **Pre-processing**: misc. text processing tips (2)

- **Info**: diversity of individual characters in tweets can prevent our parsing rules from working as intended (i.e. string matching, parsing syntax)
- **Examples**: emojis, non-latin alphabet letters, rare unicode symbols, etc.
- **Heavy-handed catch-all:** unidecode tries to replace non-ascii characters with their ascii counterparts, otherwise it removes the characters:

```
pip install unidecode
```

**Input**:

“Tina Fey & Amy Poehler 😊 #goldenglobes”

**Code**:

```
import unidecode

new_text = unidecode(original_text)
```

**Output**:

“Tina Fey & Amy Poehler #goldenglobes”

# **Pre-processing**: misc. text processing tips (3)

- URLs are common in the data – it’s your choice whether to ignore them, remove them, or integrate them into your work!
    - Can detect with regular expressions

# **Pre-processing**: misc. text processing tips (4)

- Extra whitespace can also mess with string matching / regex patterns
- Tabs and newline characters are uncommon and can usually be replaced by a single space without affecting tweet meaning / syntax
- I'd recommend this one too, but it's up to you!

**Code to substitute all whitespace**:

```
fixed = " ".join(original_text.split())
```

**Code to keep tabs/newline characters**:

```
import re

fixed = re.sub(' +', ' ', original_text)
```

# **Pre-processing**: misc. text processing tips (5)

- Most of our tweets are in English, but a sizable fraction of the data isn’t
- Detecting and removing non-English can be helpful; can often misclassify, though
- **Rule of thumb:** use confidence of language detectors to choose when to discard/keep an example
- There are a few libraries that do language detection – I’ve had the some success with pycld3:

```
pip install pycld3
```

**Input**:
'Qué tal? Qué impresiones tienen de la alfombra roja de los #GoldenGlobes ???'

**Code**:

```
import cld3

tweet_lang = cld3.get_language(tweet)
```

**Output**:

```
LanguagePrediction(
    language='es',
    probability=0.996…,
    is_reliable=True,
    proportion=1.0
)
```

# Tweet-specific features

# **Framing**: capitalizing on tweet-specific properties

- Hashtags and account names are information-rich
- Handling/leveraging quote-tweets and re-tweets is powerful
  - If something is re-tweeted a lot, it’s probably important to the project tasks
  - Unique parsing rules and types of additional analysis can be performed with quote tweets
- Syntax of tweets can throw off 3rd party tools you might want to use. Examples:
  - Syntactic parsers (e.g. if you want to use part-of-speech tagging) – these often use statistical models that are probably trained on standard text
  - Language detection models – our dataset has a lot of non-English text

… **TL;DR:** even if we don’t build features around these, useful for cleaning our data

# **Hashtags + usernames**: motivation

- #/@’s are easy to extract from text
  - Limited to alphanumeric characters + underscore → easily found with regular expressions
  - No spaces allowed → certainty that we have the full hashtag or username
- #/@’s are often easy to convert into natural language
  - Most of the high-frequency #/@’s are CamelCase or snake_case (more on that later)
  - For lower-case multi-word ones, we can use context to resolve them
  - Example – counts of hashtags that match any casing of “SelmaMovie”:

```
{'#SelmaMovie': 4424, '#selmamovie': 259, '#SELMAmovie': 4, '#SELMAMOVIE': 2}
```

# **Hashtags + usernames**: motivation

- @’s are meaningful! 1-to-1 link to a person/organization/entity/other
  - Famous people tend to have usernames similar to their real name
  - Outliers exist: Amy Poehler == @smrtgrls
  - But, despite 1-to-1 link, people still make typos with usernames too!
- #’s are meaningful! Hashtag popularity implies trending/important things
  - Useful task-related information, e.g. #BestPicture
    - Could even use hashtag co-occurrence to build a weighted graph!
  - Contrast with usernames: no guaranteed 1-to-1 relations; ability to link hashtags is useful
    - Example: #OITNB & #OrangeIsTheNewBlack

# **Hashtags + usernames**: syntactic roles

The way that #/@’s are used in tweets typically fits into a limited set of cases

1. Using #/@’s within the context of natural language
    - Example: “I wanna see #AmyPoehler win one of these days for #ParksandRec”
    - To convert to “standard” text (code for this on the next slide):
        - For each hashtag/username, capitalization indicates where to insert spaces
        - Substitute these back into the tweet

# **Hashtags + usernames**: parsing example

This code works for references that are either CamelCase or snake_case

For other capitalization patterns: check if we’ve previously seen other hashtags with the same text + different casing

**Code:**

```
import re
from inflection import humanize, underscore

usernames = re.findall(r“@(\w+)”, tweet_text)
hashtags = re.findall(r“#(\w+)”, tweet_text)

for part_list in [usernames, hashtags]:
      processed_parts = []
      for part in part_list:
            snake_name = part[:] if “_” in part else underscore(part)
            processed_parts.append(humanize(snake_name))
```

**Example input strings → output strings:**

#BestDirector → Best director
#best_director → Best director
#bestdirector → Bestdirector

# **Hashtags + usernames**: syntactic roles

2. Denoting the original tweet author in the context of retweets/quote tweets
    - "Aaand now I'm mad. RT @goldenglobes: Best Motion Picture - Comedy or Musical - Les Miserables - #GoldenGlobes"

To make analysis easier, use the “RT @...” to split the full string:

- The retweeted text → *Best Motion Picture …*
    - Suggestion: store the retweeted text and the original username – easier to track how often the original tweet was RT’d
- Any newly added text → *Aaand now I'm mad.*

# **Hashtags + usernames**: syntactic roles

3. Username-specific: tweeting at / tagging another account

> "@joshuahorowitz RT @goldenglobes: From the pressroom: Jodie Foster says that she's not retiring from acting. ... http://t.co/a48rr4e2"
>
> “@EmWatson you're so right is doesn't get better than this :) #GoldenGlobes”

# **Hashtags + usernames**: syntactic roles

4. Inserted outside of any natural language context (and not fitting into cases 2/3)

"Django wins it's first award!  #BestSupportingActor #GoldenGlobes"

… Beware of edge cases! This one is tricky to partition:

"#DjangoUnchained and Quentin Tarantino reeling in the #GoldenGlobes #Deserving #BestFilm"

(suggestion: syntax parsing!)

# **One application**: improving language detection

Language detection accuracy drops in the presence of hashtags and usernames

- In this example, the hashtags aren’t integral to the natural language’s syntax

Example on the right: **misclassified as Danish!**

**Input**:

“All these hot men in tuxes... I love it. Ben affleck, Hot! #eredcarpet #GoldenGlobes”

**Output**:

```
LanguagePrediction(
    language='da',
    probability=0.476…,
    is_reliable=False,
    proportion=1.0
)
```

# **One application**: improving language detection

Dropping the hashtags fixes the output!

**New input**:
"All these hot men in tuxes... I love it. Ben affleck, Hot!"

**New output**:

```
LanguagePrediction(
    language='en',
    probability=0.905…,
    is_reliable=True,
    proportion=1.0
)
```

**Input**:
"All these hot men in tuxes... I love it. Ben affleck, Hot! #eredcarpet #GoldenGlobes"

**Output**:

```
LanguagePrediction(
    language='da',
    probability=0.476…,
    is_reliable=False,
    proportion=1.0
)
```

# **Re-tweets + quote tweets**: motivation

RT/QTs are fairly straightforward to detect and parse – cases:

1. Simple retweet: tweet starts with “RT @”
   a. “RT @goldenglobes: Best Director - Ben Affleck (@BenAffleck) - Argo - #GoldenGlobes”
2. Simple quote tweet: includes “ RT @” (note the space before “RT”!)
   a. “Congratz beautiful! RT @TVGuide: Best actress for comedy/musical goes to Jennifer Lawrence #GoldenGlobes”
3. Can retweet/quote tweet existing retweets/quote tweets
   a. "RT @AmazedByRobsten: RT @goldenglobes: From the pressroom: Jodie Foster says that she's not retiring from acting. She's looking forward to directing more."
   b. “RT @MsAmberPRiley: Truth RT @bernardx: you could hear a pin drop. Who else can command that kind of respect and admiration. Very few.#GoldenGlobes”
4. Other QT formats exist, though – e.g. [added text] “@username …”

# **Re-tweets + quote tweets**: motivation

RTs are meaningful!

a. Expression of agreement/interest/etc.
b. Can suggest importance of the **content** of the original tweet
   i. Tracking the number of retweets for each original tweet could be very useful
   ii. More retweets → information in original tweet is more likely to be reliable
c. Can suggest importance of the **account** of the original tweet
   i. Most retweeted accounts in GG2013 include the official Golden Globes account, news organizations, etc.
   ii. Lots of different ways to use this in your analysis!

# **Re-tweets + quote tweets**: motivation

QTs are meaningful!

a. QTs can be used to measure importance, like RTs
b. Structurally, QTs guarantee that the text of the quote tweet is directly related to the content of the original tweet
    i. If some tweet is quote-tweeted a reasonable amount, the added texts in QTs can be a cheap way to get overall reactions to something – e.g. were there any nominees who really got snubbed for an award?
    ii. The average length of added text in QTs is much shorter than standard tweets – additional tasks like sentiment analysis are especially good fits

# **Re-tweets + quote tweets**: motivation

QTs are meaningful!

a. QTs can be used to measure importance, like RTs
b. Structurally, QTs guarantee that the text of the quote tweet is directly related to the content of the original tweet
c. QT-specific parsing rules can be interesting and useful!
    i. Linking awards + other project tasks:
        - "Boo Brave. It's all about #WreckItRalph RT @CNNshowbiz: Best animated film is awarded to \"Brave\" #GoldenGlobes"
        - ^ likely that “#WreckItRalph” is a nominee for “Best animated film”
    ii. Sentiment analysis related to specific awards/events/etc.:
        - "Yes!! I am SO happy for Anne! RT @goldenglobes Best Supporting Actress in a Motion Picture - Anne Hathaway - Les Miserables - #GoldenGlobes"
    iii. … and more!

# **Tweet timestamp**: motivation

- Our data also includes “timestamp_ms” for each tweet == when the tweet was posted
- Consider a stripped-down script of the progression of award shows:
  - People arrive – often a red carpet-type thing
  - The show starts – hosts introduce themselves
  - Awards are presented sequentially
  - The show ends

# **Tweet timestamp**: motivation

- These script events afford specific types of things we can learn/extract:
  - People arrive – often a red carpet-type thing
    - Can learn what people are wearing (who is best dressed?), who arrives or takes pictures together, etc.
    - Can learn about award names, nominees, hosts (likely released before the show)
    - *Cannot* learn about award winners! Could ignore all tweets from this part of this script for winner-related parsing rules
  - The show starts – hosts introduce themselves
  - Awards are presented sequentially
  - The show ends

# **Tweet timestamp**: motivation

- These script events afford specific types of things we can learn/extract:
  - People arrive – often a red carpet-type thing
  - The show starts – hosts introduce themselves
    - My intuition is that the number of host-related tweets dramatically increases here
    - Still no award winners to parse, yet!
  - Awards are presented sequentially
  - The show ends

# **Tweet timestamp**: motivation

- These script events afford specific types of things we can learn/extract:
  - People arrive – often a red carpet-type thing
  - The show starts – hosts introduce themselves
  - Awards are presented sequentially
    - Intuition: tweets related to each award name/nominees/winners/presenters spike when each award’s phase starts
    - Trivially: we can only know the winner of an award once we reach its individual presentation → can turn on winner-related parsing rules
  - The show ends

# **Tweet timestamp**: motivation

- All to say – extremely useful to estimate the timing of these events:
    - Start of actual award show
    - The start and end times for each award
        - During this range (and immediately after): more likely that tweets are about the award
            - Example use case: merging shortened forms / typos / etc. related to award names
            - Concretely: suppose that you extract “best movie”, “best film”, “best picture” from tweets in a specific award’s window
            - Then, we can be more confident that those expressions refer to the same award!
        - If less confident about some candidate parses related to names of awards, do those potential answers resolve any “gaps” in your estimated schedule for all awards?

# **Tweet timestamp**: processing raw timestamps

- Each example has a POSIX timestamp (time since Jan 1 1970) in milliseconds
- We can use python’s built-in datetime library to easily parse it into a human-readable format

**Code**:

```
import datetime



raw_time = example["timestamp_ms"]

dt = datetime.datetime.fromtimestamp(raw_time/1000.0)
```