Figurative Language Processing in Social Media: Humor Recognition and Irony Detection

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Objective

- Develop a linguistic-based framework for figurative language processing.
- In particular, figurative language concerning two independent tasks:
  - Humor recognition.
  - Irony detection.
- Identify figurative uses of both devices in social media texts.
  - Non prototypical examples at textual level.
One-liners (very short texts): any pattern?

- Jesus saves, and at today’s prices, that’s a miracle!
- Love is blind, but marriage is a real eye-opener.
- Drugs may lead to nowhere, but at least it’s a scenic route.
- Become a computer programmer and never see the world again.
- My software never has bugs; it just develops random features.
- God must love stupid people. He made so many of them.
Humor recognition: some hints

- **Antonyms**
  - Love is *blind*, but marriage is a real *eye-opener*.

- **Human weakness**
  - Drugs may lead to nowhere, but at least it’s a scenic route.

- **Common topics — communities**
  - Become a *computer programmer* and never see the world again.

- **Ambiguity**
  - Jesus *saves*, and at today’s prices, that’s a miracle!

- **Irony**
  - God must love *stupid people*. He made so many of them.
Irony detection: coarse or fine-grained? Irony, sarcasm or satire?

- If you find it hard to laugh at yourself, I would be happy to do it for you.
- God must love stupid people. He made so many of them.
Irony detection in social media: Twitter

- Toyota’s new slogan ;moving forward (even if u don’t want to); hahahaha :)
- 'Toyota; moving forward.' Yeah because you have faulty brakes and jammed accelerators. :P
- My car broke down! Noooooooooo! I bought a Toyota so that it wouldn’t brake down.:(
- CERN recruiting engineers from Toyota for further improvements to their particle accelerator :P iamconCERNed
Research Questions

▶ How to differentiate between literal language and figurative language (theoretically and automatically)?

▶ How to identify phenomena whose primary attributes rely on information beyond the scope of linguistic arguments?

▶ What are the formal elements (at linguistic level) to determine that any statement is funny or ironic?

▶ If figurative language is not only a linguistic phenomenon, then how useful is to define figurative models based on linguistic knowledge?

▶ Is there any applicability beyond lab (ad hoc) scenarios concerning figurative language, especially, concerning humor and irony?
Literal Language

- Notion of true, exact or real meaning.
- A word (isolated or within a context) conveys one single meaning.
- Meaning is invariant in all contexts.

- *Flower*
  - Same meaning in all contexts.
  - Senseless beyond its main referent.
  - Poetry, evolution.
  - Meaning cannot be deviated
Figurative Language

- Literally = 🌸

- Figuratively may refer to secondary referents:
  
  ![Female symbol](gender.png) ![Peace symbol](peace.png) ![Beauty](beauty.png)

- Secondary referents are not necessarily related to the main referent.
- Figurative meaning is not given a priori, it must be implicated.
- Intentionality.
Humor

- Amusing effects, such as laughter or well-being sensations.
- Main function is to release emotions, sentiments or feelings.
- Various categories.

- Verbal humor.
- Linguistic approach.
- Linguistic mechanisms to generate humor.
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  - Change is inevitable, except from a vending machine (ambiguity).
  - God must love stupid people. He made so many of them. (irony).
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Irony

- Opposition of what it is literally said.
- Most studies have a linguistic approach.
- Verbal irony.
- Conflicting frames of reference.
  - I feel so miserable without you, it’s almost like having you here.
  - Don’t worry about what people think. They don’t do it very often.
  - Sometimes I need what only you can provide: your absence.
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- Quite related to devices such as sarcasm, satire, or even humor.
- Experts often consider subtypes of irony (Colston, Gibbs, Attardo).

Operational Definition: Linguistic device in which there is opposition between what it is literally communicated and what it is figuratively implicated.

- **Aim**: communicate the opposite of what is literally said.
- **Effect**: sarcastic, satiric, or even funny interpretation.
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- May be considered as a subfield of Natural Language Processing.
- Focused on finding formal elements to computationally process figurative uses of natural language.
- State of the art.
  - Humor generation & recognition.
    - Phonological, incongruity, semantics (Binsted, Mihalcea, Strapparava).
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  - Non-factual information that is linguistically expressed.
  - Represent salient attributes of humor and irony, respectively.
  - *What casual speakers believe to be humor and irony in a social media text.*
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- Focused on non prototypical (ad hoc) examples.
- Theory does not often match *real examples*.
- Particularities support generalities.

- Model evaluation.
- Sparse (null) data.
  - Subjective task.
  - Personal decisions.
  - *Concrete boundaries do not exist for casual speakers.*
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Humor Recognition Model

- Advances in humor processing.
- More complex linguistic patterns.
  - What do you use to talk an elephant? An elly-phone.
  - Infants don’t enjoy infancy like adults do adultery.
- Ambiguity.
  - Two or more possible interpretations.
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- Ambiguity-based patterns.
  - Lexical.
    - Drugs may lead to nowhere, but at least it’s a scenic route.
  - Morphological.
    - Customer: I’ll have two lamb chops, and make them lean, please. Waiter: To which side, sir?
  - Syntactic.
    - Parliament fighting inflation is like the Mafia fighting crime.
  - Semantic.
    - Jesus saves, and at today’s prices, that’s a miracle!
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- Lexical.
  - Predictable sequences of words.
  - *Bank*: financial - money, checks, etc.
  - Perplexity.

\[ PP(W) = \sqrt[N]{\frac{1}{P(w_1w_2\ldots w_N)}} \]

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First Evaluation

- Frequency of patterns.
- Data sets used in humor processing.
  - H1. Italian quotations. Size 1,966.
  - H2. English one-liners. Size 16,000.
- How well the set of patterns matches two types of discourses.
- Hints about the presence of ambiguity-based patterns in humor.
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- Preliminary findings
  - Romance languages such as Italian (H1) and Catalan (H3) seem to be less predictable than English (H2).
  - Humorous statements, on average, often use verbs and nouns to produce ambiguity.
  - Different interpreting frames tend to generate humor.
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- Adding surface patterns.
  - Humor Domain.
  - Polarity.
  - Templates.
  - Affectiveness
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Second Evaluation

- New data set
  - Collected from LiveJournal.com

- Goal: classify texts into the data set they belong to.

- Humor Average Score.
  1. Let \((p_1 \ldots p_n)\) be HRM’ patterns, concerning both ambiguity-based and surface patterns.
  2. Let \((b_1 \ldots b_k)\) be the set of documents in H4, regardless of the subset they belong to.
  3. If \(b_k \left( \frac{\sum p_1 \ldots p_n}{|B|} \right) \geq 0.5\), then humor average for \(b_k\) was = 1.
  4. Otherwise, humor average was = 0.
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Insights

- Results comparable to the ones reported in previous research works.
- Some sets seem to have a lot of humorous content.
  - Intrinsic task complexity.
- Humor’s psychological branch.
  - Do we laugh for not suffering?
- Specialized contents (Wikipedia) are well discriminated.
- Not all the patterns are equally relevant.

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<th>FEATURE</th>
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<tr>
<td>1</td>
<td>Lexical ambiguity</td>
<td>PPL</td>
</tr>
<tr>
<td>2</td>
<td>Domain</td>
<td>Adult slang, wh-templates, relationships, nationalities</td>
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<tr>
<td>3</td>
<td>Semantic ambiguity</td>
<td>Semantic dispersion</td>
</tr>
<tr>
<td>4</td>
<td>Affectiveness</td>
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<td>Morphological ambiguity</td>
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Basic IDM

- First approach.
- Low level patterns.
  - N-grams: frequent sequences of words.
  - Descriptors: tuned up sequences of words.
  - POS n-grams: POS templates.
  - Polarity: underlying polarity.
  - Affectiveness: emotional content.
  - Pleasantness: degree of pleasure.

- Data set I1.
- User-generated tags: wisdom of the crowd.
- Viral effect: Amazon products.

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<td>Type</td>
<td>Reviews</td>
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<td>Amazon</td>
<td>Slashdot</td>
<td>TripAdvisor</td>
</tr>
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Wisdom of Crowd

Customer Reviews
The Mountain Three Wolf Moon Short Sleeve Tee

2,155 Reviews

<table>
<thead>
<tr>
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<th>Count</th>
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<tbody>
<tr>
<td>5 star</td>
<td>(1,747)</td>
</tr>
<tr>
<td>4 star</td>
<td>(145)</td>
</tr>
<tr>
<td>3 star</td>
<td>(64)</td>
</tr>
<tr>
<td>2 star</td>
<td>(42)</td>
</tr>
<tr>
<td>1 star</td>
<td>(157)</td>
</tr>
</tbody>
</table>

Average Customer Review: 4.5 stars (2,155 customer reviews)

Search Customer Reviews

The most helpful favorable review:

⭐⭐⭐⭐⭐ Dual Function Design
This item has wolves on it which makes it intrinsically sweet and worth 5 stars by itself, but once I tried it on, that's when the magic happened. After checking to ensure that the shirt would properly cover my girth, I walked from my trailer to Wal-mart with the shirt on and was immediately approached by women. The women knew from the wolves on my shirt that I, like a...

Read the full review>

Published on November 10, 2008 by B. Govern

The most helpful critical review:

⭐⭐⭐⭐⭐ May have side effects
The effect that this t-shirt has on women is pretty impressive. Unfortunately its natural healing powers reversed my vasectomy and I impregnated nine women in two weeks before I realized. They all had twin boys. Now I have 18 sons and spend most of my money on child support and condoms.

Published on May 29, 2009 by Frank

See more 3 star, 2 star, 1 star reviews

See more 5 star, 4 star reviews

This product

The Mountain Three Wolf Moon Short Sleeve Tee by The Mountain

$36.00 - $26.96

Add to Wish List

See buying options

Online Reputation
Irony: Beyond a Funny Effect

- Irony and humor tend to overlap their effects.
- Both devices share some similarities (logic entailment).
- They **cannot** be treated as the same device, neither theoretically nor computationally.
- Evaluate HRM’s capabilities to accurately classify instances of irony.
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  - POS n-grams
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\[ \delta_{i,j}(d_k) = \frac{f_{df_i,j}}{|d|} \]

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- Basic properties of irony.
- Close related to humor patterns.
- Scope limited.
- Fine-grained patterns.
- Improve basic IDM.
- Four complex patterns
  - **Signatures**: concerning pointedness, counter-factuality, and temporal compression.
  - **Unexpectedness**: concerning temporal imbalance and contextual imbalance.
  - **Style**: as captured by character-grams (c-grams), skip-grams (s-grams), and polarity skip-grams (ps-grams).
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Evaluation

- **New data set** I2
- **User-generated tags**: #irony.

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<th></th>
<th>#irony</th>
<th>#education</th>
<th>#humor</th>
<th>#politics</th>
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</thead>
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</tr>
<tr>
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<td>138,056</td>
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- **Two distributions.**
  - Balanced: (50/50).
  - Imbalanced: (30/70).
Results

▸ Balanced.

(a)

(b)

(c)

▸ Imbalanced.

(a)

(b)

(c)
Insights

- Accuracy higher than the baseline (75%).
- Similar results reported in previous research works (44.88% to 85.40%).
  - Focused on sarcasm, satire.
  - Not entirely comparable to the current results.
- Four conceptual patterns cohere as a single framework.
  - No much higher than the baseline (70%).
  - 6% higher than the baseline.
    - Difficulty when irony data are very few.
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- If funny comments are retrieved accurately, they would be of a great entertainment value for the visitors of a given web page.

- 600,000 funny web comments from Slashdot.org.

- Four classes: funny vs. informative (c1), insightful (c2), negative (c3).

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Online Reputation

- Enterprises have direct access to negative information.
- More difficult to mine knowledge from positive information that implies a negative meaning.
- Detect ironic tweets concerning opinions about #toyota.
  - New #toyota Tshirt: once you drive on you’ll never stop :)  
  - Love is like a #Toyota; it can’t be stopped.
- IDM vs. Human annotators
  - Three ironic representative thresholds (A = 1; B = 0.8; C = 0.6).
  - The closer to 1, the more restricted model.
- Annotators agree on 147 ironic tweets of 500.
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- Annotators agree on 147 ironic tweets of 500.

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Main Conclusions

- Model representation is given by analyzing the linguistic system as an integral structure.
- Fine-grained patterns to mine valuable knowledge.
- Scope enhanced by considering casual examples of humor and irony.
- Methodology to foster corpus-based approaches.
- No single pattern is distinctly humorous or ironic.
  - All together provided a valuable linguistic inventory for detecting both figurative devices at textual level.
Further Directions

- Improve the quality of textual patterns.
- Fine-grained representation.
  - Sarcasm.
- Comparison with human judgments.
- Manually annotate large-scale examples.
- Approach FLP from different angles.
  - Cognitive and psycholinguistic information.
  - Visual stimuli of brains responses.
  - Gestural information, tone, paralinguistic cues.
Thanks


- Reyes A., P. Rosso. On the Difficulty of Automatically Detecting Irony: Beyond a Simple Case of Negation In *Knowledge and Information Systems*. 
Language

- Language is the mean by which we verbalize our reality.
- Language is not static; rather it is in constant interaction between the rules of its grammar and its pragmatic use.
- Just so language acquires its complete meaning.
- I really need some antifreeze in me on cold days like this.
- Grammatical structure is not made intelligible only by the knowledge of the familiar rules of its grammar (Fillmore et al.)
- Cognitive processes to figure out the meaning.
- Referential knowledge: antifreeze is a liquid.
- Inferential knowledge: antifreeze is a liquid, liquor is a liquid, antifreeze is a liquor.
- Language is a continuum.
- Operational bases when formalizing and generalizing language.
- NLP scenario. Need of closed (handleable) categories.
- Otherwise, language is not apprehensible = chaos
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Figure of Speech

- Tropes.
- Devices with an unexpected twist in the meaning of words.
- Similes (when something is like something else).
- Puns (play of words with funny effects).
- Oxymoron (use of contradictory words).

- Schemes.
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Semantic Dispersion

Noun

- \( S: (n) \) brake (a restraint used to slow or stop a vehicle)
  - direct hyponym / full hyponym
    - \( S: (n) \) restraint, constraint (a device that retards something's motion) "the car did not have proper restraints fitted"
  - \( S: (n) \) device (an instrumentality invented for a particular purpose) "the device is small enough to wear on your wrist; a device intended to conserve water"
    - \( S: (n) \) instrumentality, instrumentation (an artifact or system of artifacts that is instrumental in accomplishing some end)
      - \( S: (n) \) artifact, artefact (a man-made object taken as a whole)
        - \( S: (n) \) whole, unit (an assemblage of parts that is regarded as a single entity) "how big is that part compared to the whole?"; "the team is a unit"
    - \( S: (n) \) object, physical object (a tangible and visible entity; an entity that can cast a shadow) "it was full of rackets, balls and other objects"
      - \( S: (n) \) physical entity (an entity that has physical existence)
        - \( S: (n) \) entity (that which is perceived or known or inferred to have its own distinct existence (living or nonliving))

1º common hypernym
\( \hat{S}(w_1) = 6 \)

- derivationally related form
- \( S: (n) \) brake (any of various ferns of the genus Pteris having pinnately compound leaves and including several popular houseplants)
  - member holonym
  - direct hypernym / inherited hypernym / sister term
    - \( S: (n) \) fern (any of numerous flowerless and seedless vascular plants having true roots from a rhizome and fronds that uncurl upward; reproduce by spores)
      - \( S: (n) \) pteridophyte, nonflowering plant (plants having vascular tissue and reproducing by spores)
        - \( S: (n) \) vascular plant, tracheophyte (green plant having a vascular system: ferns, gymnosperms, angiosperms)
          - \( S: (n) \) plant, flora, plant life (botany) a living organism lacking the power of locomotion
            - \( S: (n) \) organism, being (a living thing that has (or can develop) the ability to act or function independently)
              - \( S: (n) \) living thing, animate thing (a living (or once living) entity)
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1º common hypernym
\( \hat{S}(w_2) = 8 \)
Weighting Patterns?

- No all the patterns are equally discriminating.
- Weights and penalties to tune up the models.
- Some better results when specific data sets are used (Twitter).
- Particularizing vs. Generalizing.
- One (tuned up) model - one (ad hoc) data set.
- The less restricted, the wider applicability.
Representativeness

- When evaluating representativeness we look to whether individual patterns are linguistically correlated to the ways in which users employ words and visual elements when speaking in a mode they consider to be ironic.

\[ \delta_{i,j}(d_k) = \frac{fdf_{i,j}}{|d|} \]

- where \( i \) is the \( i \)-th feature (\( i = 1 \ldots 4 \));
- \( j \) is the \( j \)-th dimension of \( i \) (\( j = 1 \ldots 2 \) for unexpectedness, and \( 1 \ldots 3 \) otherwise);
- \( fdf \) (feature dimension frequency) is the frequency of dimension \( j \) of feature \( i \); and \( |d| \) is the length (in terms of tokens) of the \( k \)-th document \( d_k \).
Aid Understanding

- **HAHAHAHA!!!** now thats the definition of !!! lol...tell him to kick rocks!

- **Pointedness, $\delta = 0.85$**

- $(HAHAHAHA, !!!, !!!, lol, \ldots, !) \div (hahahaha, now, definit, lol, tell, kick, rock)$.

- **Counter-factuality, $\delta = 0.$**

- **Temporal-compression, $\delta = 0.14$**

- $(now) \div (hahahaha, now, definit, lol, tell, kick, rock)$.

- This process is applied to all dimensions for all four features.

- Once $\delta_{i,j}$ is obtained for every single $d_k$, a representativeness threshold is established in order to filter the documents that are more likely to have ironic content.

- **Ironic average threshold $= 0.5$**
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- **Pointedness**
  - The govt should investigate him thoroughly; do I smell IRONY
  - Irony is such a funny thing :)
  - Wow the only network working for me today is 3G on my iPhone. WHAT DID I EVER DO TO YOU INTERNET???????

- **Counter-factuality**
  - My latest blog post is about how twitter is for listening. And I love the irony of telling you about it via Twitter.
  - Certainly I always feel compelled, obsessively, to write. Nonetheless I often manage to put a heap of crap between me and starting ...
  - BHO talking in Copenhagen about global warming and DC is about to get 2ft. of snow dumped on it. You just gotta love it.

- **Temporal compression**
  - @ryan_onnolly oh the irony that will occur when they finally end movie piracy and suddenly movie and dvd sales begin to decline sharply.
  - I’m seriously really funny when nobody is around. You should see me. But then you’d be there, and I wouldn’t be funny...
  - RT @ButlerGeorge: Suddenly, thousands of people across Ireland recall that they were abused as children by priests.
Temporal imbalance

- Stop trying to find love, it will find you;...and no, he didn’t say that to me..
- Woman on bus asked a guy to turn it down please; but his music is so loud, he didn’t hear her. Now she has her finger in her ear. The irony

Contextual imbalance

- DC’s snows coinciding with a conference on global warming proves that God has a sense of humor. Relatedness score of 0.3233
- I know sooooo many Haitian-Canadians but they all live in Miami. Relatedness score of 0
- I nearly fall asleep when anyone starts talking about Aderall. Bullshit. Relatedness score of 0.2792
Character n-grams (c-grams)

- **WIF**
  More about Tiger - Now I hear his *wife* saved his life w/ a golf club?

- **TRAI**
  SeaWorld (Orlando) *trainer* killed by killer whale. or reality? oh, I’m sorry politically correct Orca whale

- **NDERS**
  Because common sense isn’t so common it’s important to engage with your market to really *understand* it.

Skip-grams (s-grams)

- 1-skip: *richest ... mexican*
  Our president is black nd the *richest* man is a *Mexican* hahaha hahaha lol

- 2-skips: *love ... love*
  Why is it the Stockholm syndrome if a hostage falls in *love* with her kidnapper? I’d simply call this *love*. ;)

Polarity s-grams (ps-grams)

- 1-skip: *pos-neg*
  Reading *glasses* *pos* have *RUINED* *neg* my eyes. B4, I could see some shit but I’d get a headache. Now, I can’t see shit but my head feels fine

- 2kips: *pos-pos-neg*
  Just heard the *brave* *pos* *hearted* *pos* English Defence *League* *neg* thugs will protest for our freedoms in Edinburgh next month. Mad, Mad, Mad
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- **Activation**
  - My favorite part of the optometrist is the irony of the fact that I can't see afterwards. That and the cool sunglasses.
  - My male ego so eager to let it be stated that I am THE MAN but won't allow my pride to admit that being egotistical is a weakness ...

- **Imagery**
  - Yesterday was the official first day of spring ... and there was over a foot of snow on the ground.
  - I think I have to do the very thing that I work most on changing in order to make a real difference paradigms shifts zeitgeist
  - Random drug test today in elkhart before 4. Would be better if I could drive. I will have to drink away the bullshit this weekend. Irony.

- **Pleasantness**
  - The guy who called me Ricky has a blind lunch date.
  - I hope whoever organized this monstrosity realizes that they're playing the opening music for WWE's Monday Night Raw at the Olympics.