Integrating Text and Image: Determining Multimodal Document Intent in Instagram Posts

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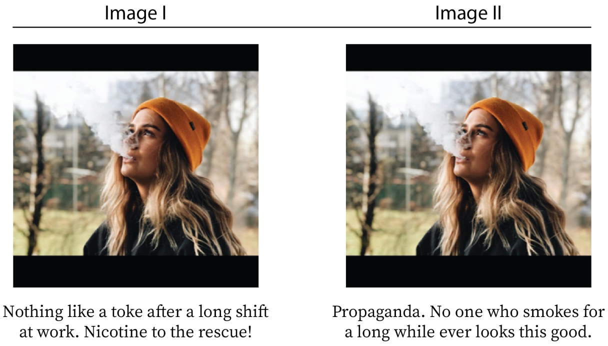
Abstract

Computing author intent from multimodal data like Instagram posts requires modeling a complex relationship between text and image. For example, a caption might evoke an ironic contrast with the image, so neither caption nor image is a mere transcript of the other. Instead they combine—via what has been called *meaning multiplication* Bateman (2014)—to create a new meaning that has a more complex relation to the literal meanings of text and image. Here we introduce a multimodal dataset of 1299 Instagram posts labeled for three orthogonal taxonomies: the authorial intent behind the image-caption pair, the contextual relationship between the literal meanings of the image and caption, and the semiotic relationship between the signified meanings of the image and caption. We build a baseline deep multimodal classifier to validate the taxonomy, showing that employing both text and image improves intent detection by 9.6% compared to using only the image modality, demonstrating the commonality of non-intersective meaning multiplication. The gain with multimodality is greatest when the image and caption diverge semiotically. Our dataset offers a new resource for the study of the rich meanings that result from pairing text and image.

1 Introduction

Multimodal social platforms such as Instagram let content creators combine visual and textual modalities. The resulting widespread use of text+image makes interpreting author intent in multimodal messages an important task for NLP for document understanding.

There are many recent language processing studies of images accompanied by basic text labels or captions (Chen et al., 2015; Faghri et al., 2018, inter alia). But prior work on image–text pairs has generally been asymmetric, regarding either image or text as the primary content, and the other as mere complement. Scholars from semiotics as well as computer science have pointed out that this is insufficient; often text and image are not combined by a simple addition or intersection of the component meanings (Bateman, 2014; Marsh and Domas White, 2003; Zhang et al., 2018).



Nothing like a toke after a long shift at work. Nicotine to the rescue!

Propaganda. No one who smokes for a long while ever looks this good.

Figure 1: Image-Caption meaning multiplication: A change in the caption completely changes the overall meaning of the image-caption pair.

Rather, determining author intent with text+image content requires a richer kind of meaning composition that has been called *meaning multiplication* (Bateman, 2014): the creation of new meaning through integrating image and text. Meaning multiplication includes simple meaning intersection or concatenation (a picture of a dog with the label “dog”, or the label “Rufus”). But it also includes more sophisticated kinds of composition, such as irony or indirection, where the text+image integration requires inference that creates a new meaning. For example in Figure 1, a picture of a young woman smoking is given two different hypothetical captions that result in different composed meanings. In Pairing I, the image and text are parallel, with the picture

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used to highlight relaxation through smoking. Pairing II uses the tension between her image and the implications of her actions to highlight the dangers of smoking.

Computational models that detect complex relationships between text and image and how they cue author intent could be significant for many areas, including the computational study of advertising, the detection and study of propaganda, and our deeper understanding of many other kinds of persuasive text, as well as allowing NLP applications to news media to move beyond pure text.

To better understand author intent given such meaning multiplication, we create three novel taxonomies related to the relationship between text and image and their combination/multiplication in Instagram posts, designed by modifying existing taxonomies (Bateman, 2014; Marsh and Domas White, 2003) from semiotics, rhetoric, and media studies. Our taxonomies measure the **authorial intent** behind the image-caption pair and two kinds of text-image relations: the **contextual relationship** between the literal meanings of the image and caption, and the **semiotic relationship** between the signified meanings of the image and caption. We then introduce a new dataset, MDID (Multimodal Document Intent Dataset), with 1299 Instagram posts covering a variety of topics, annotated with labels from our three taxonomies.

Finally, we build a deep neural network model for annotating Instagram posts with the labels from each taxonomy, and show that combining text and image leads to better classification, especially when the caption and the image diverge. While our goal here is to establish a computational framework for investigating multimodal meaning multiplication, in other pilot work we have begun to consider some applications, such as using intent for social media event detection and for user engagement prediction. Both these directions highlight the importance of the intent and semiotic structure of a social media posting in determining its influence on the social network as a whole.

2 Prior Work

A wide variety of work in multiple fields has explored the relationship between text and image and extracting meaning, although often assigning a subordinate role to either text or images, rather than the symmetric relationship in media such as Instagram posts. The earliest work in the Barthesian tradition focuses on advertisements, in which the text serves as merely another connotative aspect to be incorporated into a larger connotative meaning (Heath et al., 1977). Marsh and Domas White (2003) offer a taxonomy of the relationship between image and text by considering image/illustration pairs found in textbooks or manuals. We draw on their taxonomy, although as we will see, the connotational aspects of Instagram posts require some additions.

For our model of speaker intent, we draw on the classic concept of illocutionary acts (Austin, 1962) to develop a new taxonomy of illocutionary acts focused on the kinds of intentions that tend to occur on social media. For example, we rarely see commissive posts on Instagram and Facebook because of the focus on information sharing and constructions of self-image.

Computational approaches to multi-modal document understanding have focused on key problems such as image captioning (Chen et al., 2015; Faghri et al., 2018), visual question answering (Goyal et al., 2017; Zellers et al., 2018; Hudson and Manning, 2019), or extracting the literal or connotative meaning of a post (Soleymani et al., 2017). More recent work has explored the role of image as context for interaction and pragmatics, either in dialog (Mostafazadeh et al., 2016, 2017), or as a prompt for users to generate descriptions (Bisk et al., 2019). Another important direction has looked at an image's *perlocutionary force* (how it is perceived by its audience), including aspects such as memorability (Khosla et al., 2015), saliency (Bylinskii et al., 2018), popularity (Khosla et al., 2014) and virality (Deza and Parikh, 2015; Alameda-Pineda et al., 2017).

Some prior work has focused on intention. Joo et al. (2014) and Huang and Kovashka (2016) study prediction of intent behind politician portraits in the news. Hussain et al. (2017) study the understanding of image and video advertisements, predicting topic, sentiment, and intent. Alikhani et al. (2019) introduce a corpus of the coherence relationships between recipe text and images. Our work builds on Siddiquie et al. (2015), who focused on a single type of intent (detecting politically persuasive video on the internet) and even more closely on Zhang et al. (2018), who study visual rhetoric as interaction between the image and the text slogan in advertisements. They categorize image-text relationships into parallel equivalent (image-text deliver same point at equal strength), parallel non-equivalent (image-text deliver the same point at different levels) and non-parallel (text or image alone is insufficient in point delivery). They also identify the novel issue of understanding the complex, non-literal ways in which text and image interacts. Weiland et al. (2018) study the non-literal meaning conveyed by image-caption pairs and draw on a knowledge-base to generate the gist of the image-caption pair.

3 Taxonomies

As Berger (1972) points out in discussing the relationship between one image and its caption:

> It is hard to define exactly how the words have changed the image but undoubtedly they have. (p. 28).

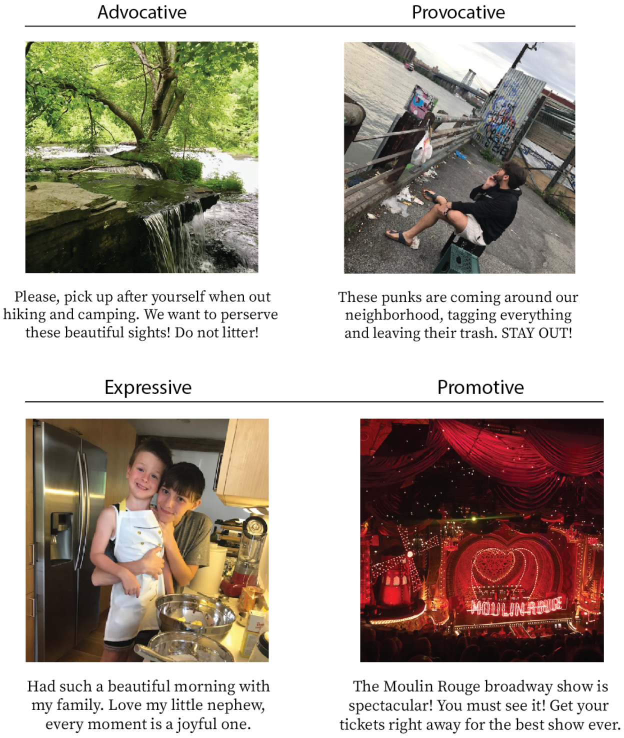
We propose three taxonomies in an attempt to answer Berger's implicit question, two (contextual and semiotic) to capture different aspects of the relationship between the image and the caption, and one to capture speaker intent.

3.1 Intent Taxonomy

The proposed intent taxonomy is a generalization and elaboration of existing rhetorical categories pertaining to illocution, that targets multimodal social networks like Instagram. We developed a set of eight illocutionary intents from our examination and clustering of a large body of representative Instagram content, informed by previous studies of intent in Instagram posts. There is some overlap between categories; to bound the burden on the annotators, however, we asked them to identify intent for the image-caption pairing as a whole and not for the individual components

For example drawing on Goffman's idea of the presentation of self (Goffman, 1978), Mahoney et al. (2016) in their study of Scottish political Instagram posts define acts like Presentation of Self, which, following Hogan (2010) we refer to as *exhibition*, or Personal Political Expression, which we generalize to *advocative*. Following are our final eight labels; Figure 2 shows some examples.

1. **advocative**: advocate for a figure, idea, movement, etc.
2. **promotive**: promote events, products, organizations etc.



Please, pick up after yourself when out hiking and camping. We want to perserve these beautiful sights! Do not litter!

These punks are coming around our neighborhood, tagging everything and leaving their trash. STAY OUT!

Had such a beautiful morning with my family. Love my little nephew, every moment is a joyful one.

The Moulin Rouge broadway show is spectacular! You must see it! Get your tickets right away for the best show ever.

Figure 2: Examples of multimodal document intent: advocative, provocative, expressive and promotive content

3. **exhibitionist**: create a self-image reflecting the person, state etc. for the user using selfies, pictures of belongings (e.g. pets, clothes) etc.
4. **expressive**: express emotion, attachment, or admiration at an external entity or group.
5. **informative**: relay information regarding a subject or event using factual language.
6. **entertainment**: entertain using art, humor, memes, etc.
7. **provocative/discrimination**: directly attack an individual or group.
8. **provocative/controversial**: be shocking.

3.2 The Contextual Taxonomy

The contextual relationship taxonomy captures the relationship between the literal meanings of the image and text. We draw on the three top-level categories of the Marsh and Domas White (2003) taxonomy, which distinguished images that are minimally related to the text, highly related to the text, and related but going beyond it. These three classes— reflecting Marsh et al.'s primary interest in illustration—frame the image only as subordinate to the text. We slightly generalize the three

Intent	
Category	*# Samples*
Provocative	84
Informative	119
Advocative	97
Entertainment	310
Expositive	237
Expressive	95
Promotive	162

Semiotic	
Category	*# Samples*
Divergent	115
Additive	277
Parallel	712

Contextual Relationship	
Category	*# Samples*
Minimal	372
Close	585
Transcendent	147

Table 1: Counts of different labels in the Multimodal Document Intent Dataset (MDID).

top-level categories taxonomy of Marsh and Domas White (2003) to make them symmetric for the Instagram domain:

Minimal Relationship: The literal meanings of the caption and image overlap very little. For example, a selfie of a person at a waterfall with the caption "selfie". While such a terse caption does nevertheless convey a lot of information, it still leaves out details such as the location, description of the scene, etc. that are found in typical loquacious Instagram captions.

Close Relationship: The literal meanings of the caption and the image overlap considerably. For example, a selfie of a person at a crowded waterfall, with the caption "Selfie at Hemlock falls on a crowded sunny day".

Transcendent Relationship: The literal meaning of one modality picks up and expands on the literal meaning of the other. For example, a selfie of a person at a crowded waterfall with the caption "Selfie at Hemlock Falls on a sunny and crowded day. Hemlock falls is a popular picnic spot. There are hiking and biking trails, and a great restaurant 3 miles down the road ...".

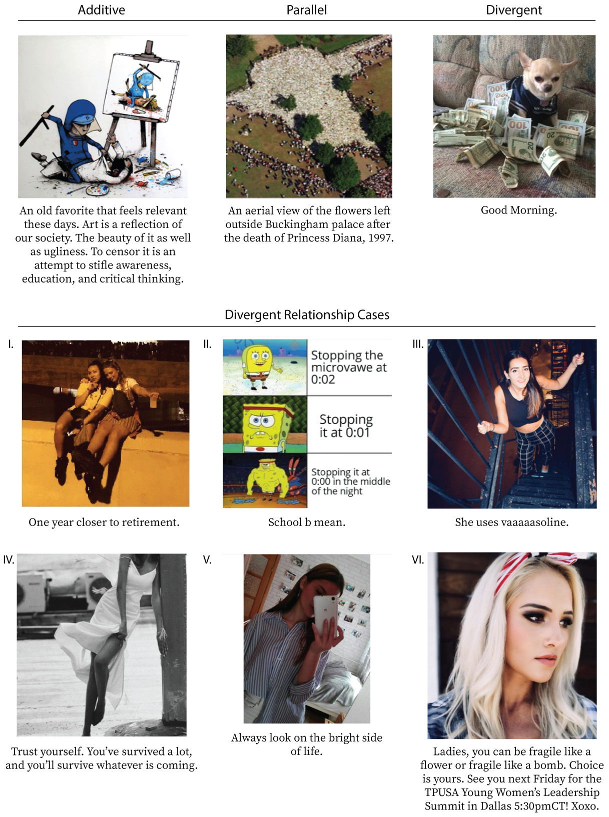
Note that while the labels "minimal" and "close" could be thought of as lying on a continuous scale indicating semantic overlap, the label "transcendent" indicates an expansion of the meaning that cannot be captured by such a continuous scale.

3.3 The Semiotic Taxonomy

The contextual taxonomy described above does not deal with the more complex forms of "meaning multiplication" illustrated in Figure 1. For example, an image of three frolicking puppies with the caption "My happy family," sends a message of pride in one's pets that is not directly reflected in either modality taken by itself. First, it forces the reader to step back and consider what is being signified by the image and the caption, in effect offering a meta-comment on the text-image relation. Second, there is a tension between what is signified (a family and a litter of young animals respectively) that results in a richer idiomatic meaning.

Our third taxonomy therefore captures the relationship between what is *signified* by the respective modalities, their *semiotics*. We draw on the earlier 3-way distinction of Kloepfer (1977) as modeled by Bateman (2014) and the two-way (parallel vs. non-parallel) distinction of Zhang et al. (2018) to classify the semiotic relationship of image/text pairs as divergent, parallel and additive. A *divergent* relationship occurs when the image and text semiotics pull in opposite directions, creating a gap between the meanings suggested by the image and text. A *parallel* relationship occurs when the image and text independently contribute to the same meaning. An *additive* relationship occurs when the image and text semiotics amplify or modify each other.

The semiotic classification is not always homologous to the contextual. For example, an image of a mother feeding her baby with a caption "My new small business needs a lot of tender loving care", would have a minimal contextual relationship. Yet because both signify loving care and the image intensifies the caption's sentiment, the semiotic relationship is additive. Or a lavish formal farewell scene at an airport with the caption "Parting is such sweet sorrow", has a close contextual relationship because of the high overlap in literal meaning, but the semiotics would be additive, not parallel, since the image shows only the leave-taking, while the caption suggests love (or ironic lack thereof) for the person leaving.


Stopping the microvawe at 0:02
Stopping it at 0:01
Stopping it at 0:00 in the middle of the night

Additive

An old favorite that feels relevant these days. Art is a reflection of our society. The beauty of it as well as ugliness. To censor it is an attempt to stifle awareness, education, and critical thinking.

Parallel

An aerial view of the flowers left outside Buckingham palace after the death of Princess Diana, 1997.

Divergent

Good Morning.

Divergent Relationship Cases

I. One year closer to retirement.

II. School b mean.

III. She uses vaaaaasoline.

IV. Trust yourself. You've survived a lot, and you'll survive whatever is coming.

V. Always look on the bright side of life.

VI. Ladies, you can be fragile like a flower or fragile like a bomb. Choice is yours. See you next Friday for the TPUSA Young Women's Leadership Summit in Dallas 5:30pmCT! Xoxo.

Figure 3: The top three images exemplify the semiotic categories. Images I-VI show instances of divergent semiotic relationships.

Figure 3 further illustrates the proposed semiotic classification. The first three image-caption pairs (ICP's) exemplify the three semiotic relationships. To give further insights into the rich complexity of the divergent category, the six ICP's below showcase the kinds of divergent relationships we observed most frequently on Instagram.

ICP I exploits the tension between the reference to retirement expressed in the caption and the youth projected by the two young women in the image to convey irony and thus humor in what is perhaps a birthday greeting or announcement. Many ironic and humorous posts exhibit divergent semiotic relationships. ICP II has the structure of a classic Instagram meme, where the focus is on the image, and the caption is completely unrelated to the image. This is also exhibited in the divergent "Good Morning" caption in the top row. ICP III is an example of a divergent semiotic relationship within an exhibitionist post. A popular communicative practice on Instagram is to combine selfies with a caption that is some sort of inside joke. The inside joke in ICP III is a lyric from a song a group of friends found funny and discussed the night this photo was taken. ICP IV is an aesthetic photo of a young woman, paired with a caption that has no semantic elements in common with the photo. The caption may be a prose excerpt, the author's reflection on what the image made them think or feel, or perhaps just a pairing of pleasant visual stimulus with pleasant literary material. This divergent relationship is often found in photography, artistic and other entertainment posts. ICP V uses one of the most common divergent relationships, in which exhibitionist visual material is paired with reflections or motivational captions. ICP V is thus similar to ICP III, but without the inside jokes/hidden meanings common to ICP III. ICP VI is an exhibitionist post that seems to be common recently among public figures on Instagram. The image appears to be a classic selfie or often a professionally taken image of the individual, but the caption refers to that person's opinions or agenda(s). This relationship is divergent—there are no common semantic elements in the image and caption—but the pair paints a picture of the individual's current state or future plans.

4 The MDID Dataset

Our dataset, MDID (the *Multimodal Document Intent Dataset*) consists of 1299 public Instagram posts that we collected with the goal of developing a rich and diverse set of posts for each of the eight illocutionary types in our intent taxonomy. For each intent we collected at least 16 hashtags or users likely to yield a high proportion of posts that could be labeled by that heading.

For the *advocative* intent, we selected mostly hashtags advocating and spanning political or social ideology such as #pride and #maga. For the *promotive* intent we relied on the #ad tag that Instagram has recently begun requiring for sponsored posts. For *exhibitionist* intent we used tags that focused on the self as the most important aspect of the post such as #selfie and #ootd (outfit of the day). The *expressive* posts were retrieved via tags that actively expressed a stance or an affective intent, such as #lovehim or #merrychristmas. Informative posts were taken from informative accounts such as news websites. Entertainment posts drew on an eclectic group of tags such as #meme, #earthporn, #fatalframes. Finally, provocative posts were extracted via tags that either expressed a controversial or provocative message or that would draw people into being influenced or provoked by the post (#redpill, #antifa, #eattherich, #snowflake).

Data Labeling: Data was pre-processed (for example to convert all albums to single image-caption pairs). We developed a simple annotation toolkit that displayed an image–caption pair and asked the annotator to confirm whether the pair was relevant (contains both an image and text in English) and if so to identify the post's intent (advocative, promotive, exhibitionist, expressive, informative, entertainment, provocative), contextual relationship (minimal, close, transcendent), and semiotic relationship (divergent, parallel, additive). Two of the authors collaborated on the labelers manual and then labeled the data by consensus, and any label on which the authors disagreed after discussion was removed. Dataset statistics are shown in Table 1; see `https://www.ksikka.com/document_intent.html` for the data.

5 Computational Model

We train and test a deep convolutional neural network (DCNN) model on the dataset, both to offer a baseline model for users of the dataset, and to further explore our hypothesis about meaning multiplication.

Our model can take as input either image (Img), text (Txt) or both (Img + Txt), and consists of modality specific encoders, a fusion layer, and a class prediction layer. We use the ResNet-18 network pre-trained on ImageNet as the image encoder (He et al., 2016). For encoding captions, we use a standard pipeline that employs a RNN model on word embeddings. We experiment with both word2vec type (word token-based) embeddings trained from scratch (Mikolov et al., 2013) and pre-trained character-based contextual embeddings (ELMo) (Peters et al., 2018). For our purpose ELMo character embeddings are more useful since they increase robustness to noisy and often misspelled Instagram captions. For the combined model, we implement a simple fusion strategy that first linearly projects encoded vectors from both the modalities in the same embedding space and then adds the two vectors. Although naive, this strategy has been shown to be effective at a variety of tasks such as Visual Question Answering (Nguyen and Okatani, 2018) and image-caption matching (Ahuja et al., 2018). We then use the fused vector to predict class-wise scores using a fully connected layer.

6 Experiments

We evaluate our models on predicting intent, semiotic relationships, and image-text relationships from Instagram posts, using image only, text only, and both modalities.

6.1 Dataset, Evaluation and Implementation

We use the 1299-sample MDID dataset (section 4). We only use corresponding image and text information for each post and do not use other meta-data to preserve the focus on image-caption joint meaning. We perform basic pre-processing on the captions such as removing stopwords and non-alphanumeric characters. We do not perform any pre-processing for images.

Due to the small dataset, we perform 5-fold cross-validation for our experiments reporting average performance across all splits. We report classification accuracy (ACC) and also area under the ROC curve (AUC) (since AUC is more robust to class-skew), using macro-average across all classes (Jeni et al., 2013; Stager et al., 2006).

We use a pre-trained ResNet-18 model as the image encoder. For word token based embeddings we use 300 dimensional vectors trained from scratch. For ELMo we use a publicly available API [1] and use a pre-trained model with two layers resulting in a 2048 dimensional input. We use a bidirectional GRU as the RNN model with 256 dimensional hidden layers. We set the dimensionality of the common embedding space in the fusion layer to 128. In case there is a single modality, the fusion layer only projects features from that modality. We train with the Adam optimizer with a learning rate of 0.00005, which is decayed by 0.1 after every 15 epochs. We report results with the best model selected based on performance on a mini validation set.

6.2 Quantitative Results

We show results in Table 2. For the intent taxonomy images are more informative than (word2vec) text (76% for Img vs 72.7% for Txt-emb) but with ELMo text outperforms just using images (82.6% for Txt-ELMo, 76.0% for Img). ELMo similarly improves performance on the contextual taxonomy but not the semiotic taxonomy.

For the semiotic taxonomy, ELMo and word2vec embeddings perform similarly, (67.8%

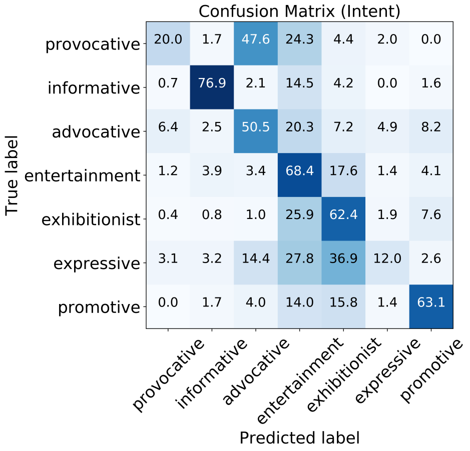
[1] `https://github.com/allenai/allennlp/blob/master/tutorials/how_to/elmo.md`

Method	Intent		Semiotic		Contextual	
	ACC	*AUC*	*ACC*	*AUC*	*ACC*	*AUC*
Chance	28.1	50.0	64.5	50.0	53.0	50.0
Img	42.9 (±0.0)	76.0 (±0.5)	61.5 (±0.0)	59.8 (±3.0)	52.5 (±0.0)	62.5 (±1.3)
Txt-emb	42.9 (±0.0)	72.7 (±1.5)	58.9 (±0.0)	67.8 (±1.7)	60.7 (±0.5)	74.9 (±3.0)
Txt-ELMo	52.7 (±0.0)	82.6 (±1.2)	61.7 (±0.0)	66.5 (±1.9)	65.4 (±0.0)	78.5 (±2.1)
Img + Txt-emb	48.1 (±0.0)	80.8 (±1.2)	60.4 (±0.0)	69.7 (±1.8)	60.8 (±0.0)	76.0 (±2.5)
Img + Txt-ELMo	56.7 (±0.0)	85.6 (±1.3)	61.8 (±0.0)	67.8 (±1.8)	63.6 (±0.5)	79.0 (±1.4)

Table 2: Table showing results with various DCNN models– image-only (Img), text-only (Txt-emb and Txt-ELMo), and combined model (Img + Txt-emb and Img + Txt-ELMo). Here *emb* is the model using standard word (token) based embeddings, while *ELMo* is the pre-trained ELMo based word embeddings (Peters et al., 2018). The numbers in Table2 are standard deviations across 5 folds.

for Txt-emb vs. 66.5% for Txt-ELMo), suggesting that individual words are sufficient for the semiotic labeling task, and the presence of the sentence context (as in ELMo) is not needed.

Combining visual and textual modalities helps across the board. For example, for intent taxonomy the joint model Img + Txt-ELMo achieves 85.6% compared to 82.6% for Txt-ELMo. Images seem to help even more when using a word embedding based text model (80.8% for Img + Txt-emb vs. 72.7% for Txt-emb). Joint models also improve over single-modality on labeling the image-text relationship and the semiotic taxonomy. We show class-wise performances with the single- and multi-modality models in Table 3. It is particularly interesting that in the semiotic taxonomy, multi-modality helps the most with divergent semiotics (gain of 4.4% compared to the image-only model).



	provocative	informative	advocative	entertainment	exhibitionist	expressive	promotive
provocative	20.0	1.7	47.6	24.3	4.4	2.0	0.0
informative	0.7	76.9	2.1	14.5	4.2	0.0	1.6
advocative	6.4	2.5	50.5	20.3	7.2	4.9	8.2
entertainment	1.2	3.9	3.4	68.4	17.6	1.4	4.1
exhibitionist	0.4	0.8	1.0	25.9	62.4	1.9	7.6
expressive	3.1	3.2	14.4	27.8	36.9	12.0	2.6
promotive	0.0	1.7	4.0	14.0	15.8	1.4	63.1

Figure 4: Confusion between intent classes for the intent classification task. The confusion matrix was obtained using the Img + Txt-ELMo model and the results are averaged over the 5 splits.

6.3 Discussion

In general, using both text and image is helpful, a fact that is unsurprising since combinations of text and image are known to increase performance on tasks such as predicting post popularity or user personality (Hessel et al., 2017; Wendlandt et al., 2017). Most telling, however, were the differences in this helpfulness across items. In the semiotic category the greatest gain came when the text-image semiotics were "divergent". By contrast, multimodal models help less when the image and text are additive, and help the least when the image and text are parallel and provide less novel information. Similarly, with contextual relationships, multimodal analysis helps the most with the "minimal" category (1.6%). This further supports the idea that on social media such as Instagram, the relation between image and text can be richly divergent and thereby form new meanings.

The category confusion matrix in Figure 4 provides further insights. The least confused category is informative. Informative posts are least similar to the rest of Instagram, since they consist of detached, objective posts, with little use of first person pronouns like "I" or "me." Promotive posts are also relatively easy to detect, since they are formally informative, telling the viewer the advantages and logistics of an item or event, with the addition of a persuasive intent reflecting the poster's personal opinions ("I love this watch".). We found that the *entertainment* label is often misapplied; perhaps to some extent all posts have a goal of entertaining, and any analysis must account for this filter of entertainment. The *Exhibitionist* intent tends to be predicted well, likely due to its visual and textual signifiers of individuality (e.g. selfies are almost always exhibitionist, as are captions

Intent			
Class	Img	Txt-ELMo	Img+ Txt-ELMo
Provocative	85.5	84.1	90.0
Informative	77.0	93.9	92.8
Advocative	84.8	82.4	87.4
Entertainment	69.0	78.6	80.5
Exhibitionist	81.7	78.7	84.9
Expressive	57.9	72.0	73.2
Promotive	76.3	88.5	90.1
Mean	76.0	82.6	85.6

Semiotic			
Class	Img	Txt-emb	Img+ Txt-ELMo
Divergent	69.8	72.7	77.1
Additive	55.0	66.7	68.2
Parallel	54.5	64.3	64.0
Mean	59.8	67.8	69.7

Contextual			
Class	Img	Txt-ELMo	Img+ Txt-ELMo
Minimal	60.9	79.7	81.3
Close	60.5	73.8	74.6
Transcendent	66.1	82.0	81.2
Mean	62.5	78.5	79.0

Table 3: Class-wise results (AUC) for the three taxonomies with different DCNN models on the MDID dataset. Except for the semiotic taxonomy we used ELMo text representations (based on the performance in Table 2).

like "I love my new hair"). There is a great deal of confusion, however, between the expressive and exhibitionist categories, since the only distinction lies in whether the post is about a general topic or about the poster, and between the provocative and advocative categories, perhaps because both often seek to prove points in a similar way.

With the contextual and semiotic taxonomies, some good results are obtained with text alone. In the "transcendent" contextual case, it is not necessarily surprising that using text alone enables 82% AUC because whenever a caption is really long or has many adverbs, adjectives or abstract concepts, it is highly likely to be transcendent. In the "divergent" semiotics case, we were surprised that text alone would predict divergence with 72.7% AUC. Examining these cases showed that many of them had lexical cues suggesting irony or sarcasm, allowing the system to infer that the image will diverge in keeping with the irony. There is, however, a consistent improvement when both modalities are used for both taxonomies.

6.4 Sample Outputs

We show some sample successful outputs of the (multimodal) model in Figure 5, in which the highest probability class in each of the three dimension corresponds to our gold labels. The top-left Image-caption pair (Image I) is classified as exhibitionist, closely followed by expressive; it is a picture of someone's home with a caption describing a domestic experience. The semiotic relationship is classified as additive; the image and caption together signify the concept of spending winter at home with pets before the fireplace. The contextual relationship is classified as transcendental; the caption indeed goes well beyond the image.

The top-right image-caption pair (Image II) is classified as entertainment; the image caption pair works as an ironic reference to dancing ("yeet") grandparents, who are actually reading, in language used usually by young people that a typical grandparent would never use. The semiotic relationship is classified as divergent and the contextual relationship is classified as minimal; there is semantic and semiotic divergence of the image-caption pair caused by the juxtaposition of youthful references with older people.

To further understand the role of meaning multiplication, we consider the change in intent and semiotic relationships when the same image of the British Royal Family is matched with two different captions in the bottom row of Figure 5 (Image IV). In both cases the semiotic relationship is parallel, perhaps due to the match between the multi-figure portrait setting and the word *family*. But the other two dimensions show differences. When the caption is "the royal family" our system classifies the intent as entertainment; presumably such pictures and caption pairs often appear on Instagram intending to entertain. But when the caption is "my happy family" the intent is classified as expressive, perhaps due to the family pride expressed in the caption.

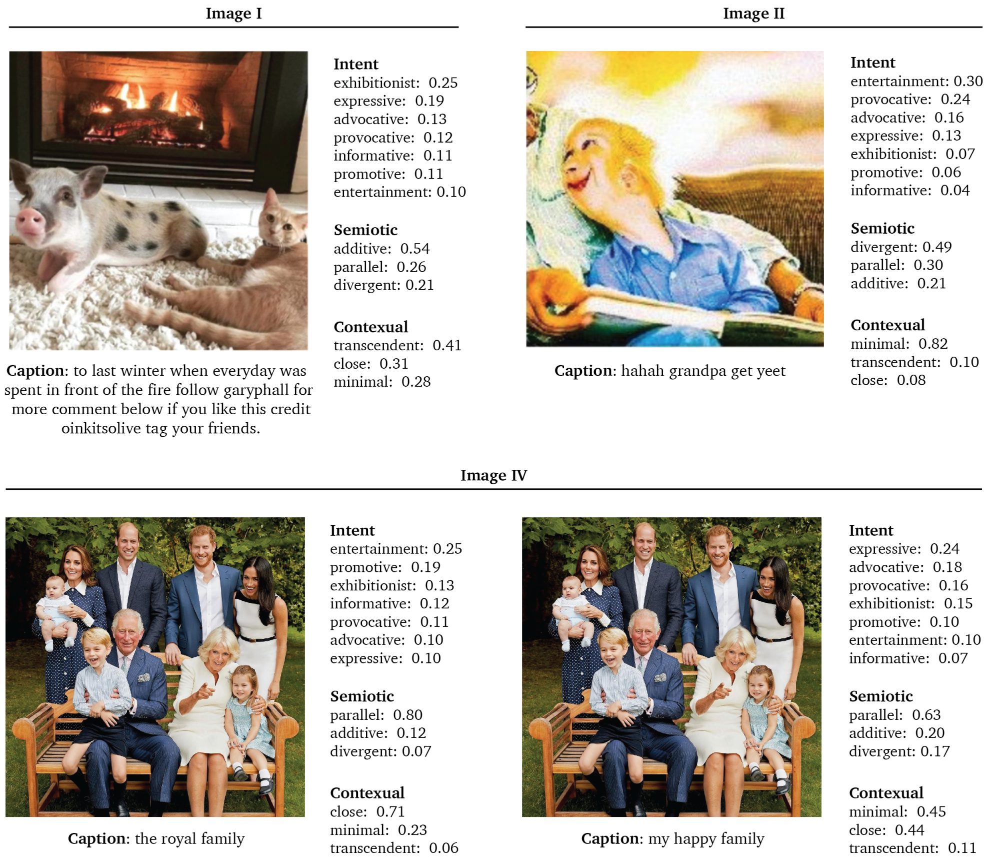


Image I

Caption: to last winter when everyday was spent in front of the fire follow garyphall for more comment below if you like this credit oinkitsolive tag your friends.

Intent
exhibitionist: 0.25
expressive: 0.19
advocative: 0.13
provocative: 0.12
informative: 0.11
promotive: 0.11
entertainment: 0.10

Semiotic
additive: 0.54
parallel: 0.26
divergent: 0.21

Contexual
transcendent: 0.41
close: 0.31
minimal: 0.28

Image II

Caption: hahah grandpa get yeet

Intent
entertainment: 0.30
provocative: 0.24
advocative: 0.16
expressive: 0.13
exhibitionist: 0.07
promotive: 0.06
informative: 0.04

Semiotic
divergent: 0.49
parallel: 0.30
additive: 0.21

Contexual
minimal: 0.82
transcendent: 0.10
close: 0.08

Image IV

Caption: the royal family

Intent
entertainment: 0.25
promotive: 0.19
exhibitionist: 0.13
informative: 0.12
provocative: 0.11
advocative: 0.10
expressive: 0.10

Semiotic
parallel: 0.80
additive: 0.12
divergent: 0.07

Contexual
close: 0.71
minimal: 0.23
transcendent: 0.06

Caption: my happy family

Intent
expressive: 0.24
advocative: 0.18
provocative: 0.16
exhibitionist: 0.15
promotive: 0.10
entertainment: 0.10
informative: 0.07

Semiotic
parallel: 0.63
additive: 0.20
divergent: 0.17

Contexual
minimal: 0.45
close: 0.44
transcendent: 0.11

Figure 5: Sample successful output predictions for the three taxonomies, showing ranked classes and predicted probabilities. In images IV the same image when paired with a different caption gives rise to a different intent.

7 Conclusion

We have proposed a model to capture the complex *meaning multiplication* relationship between image and text in multimodal Instagram posts. Our three new taxonomies, adapted from the media and semiotic literature, allow the literal, semiotic, and illocutionary relationship between text and image to be coded. Of course our new dataset and the baseline classifier models are just a preliminary effort, and future work will need to examine larger datasets, consider additional data such as hashtags, richer classification schemes, and more sophisticated classifiers. Some of these may be domain-specific. For example, Alikhani et al. (2019) show how to develop rich coherence relations that model the contextual relationship between recipe text and accompanying images (specific versions of Elaboration or Exemplification such as “Shows a tool used in the step but not mentioned in the text”). Expanding our taxonomies with richer sets like these is an important goal. Nonetheless, the fact that we found multimodal classification to be most helpful in cases where the image and text diverged semiotically points out the importance of these complex relations, and our taxonomies, dataset, and tools should provide impetus for the community to further develop more complex models of this important relationship.

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