### OVERVIEW OF THE ATTACK ALGORITHM

The algorithm consists of three functions:

- 1) Evaluate\_Word\_Saliency
- 2) Find\_Similar\_Words
- 3) Generate\_Adversary

#### Evaluate\_Word\_Saliency:

- Determine importance of each word in a review. This is done by removing one word at a time from a review and
  measuring the difference in confidence of the model before and after the word was replaced. Stop words are not
  considered.
- Words are sorted in decreasing order based on their importance. For reviews with more than words, the top three words are kept, and rest are discarded. For reviews with less than 3 words, all the words are kept.
- This function outputs a list of all salient words of a review for all reviews. Each review has at most 3 salient
  words.

### Find\_Similar\_Words:

- This function takes the salient words of the reviews computed in the previous function as input.
- For each of the salient words in a review, 50 most similar words are extracted from a pretrained fastText word embedding. The salient word in the review is replaced by each of the 50 words one at a time and fed to the model. A word is considered if:
  - Substituting the word inplace of the original word changes the prediction of the model and the adversarial review and the original review are 70% similar in context. The context similarity is determined by Universal Sentence Encoder.
  - Substituting the word inplace of the original word leads to a difference of 0.4 in the confidence of the model for the true label compared to the original confidence and is 70% similar in context as mentioned above.
  - Substituting the word inplace of the original word leads to the maximum difference in the confidence of the model for the true label compared to the original confidence and is 70% similar in context as mentioned above.

The first similar word that satisfies any of the first two conditions are considered and the process is stopped for that salient word. If none of the similar words satisfy any of the first two conditions then, the word that satisfies the third condition is picked.

• This function outputs the most similar word for a salient word of a review. From the last function, we know that each review has at most 3 salient words. And each salient word has similar words.

### • Generate\_Adversary:

- This function takes in the output of the previous function as input. We have at most 3 salient words for a review. The goal is to replace only one word from the original review.
- For a review, each of the salient words are replaced by their corresponding similar words and fed into the model. The salient word whose similar word changes the prediction of the model as well as have a 70% similarity in context to the original review is considered and the process is stopped. If no such word exists, then the salient word whose similar word leads to the maximum difference in the confidence of the model and have a 70% similarity in context to the original review is considered.

This algorithm is based on word saliency and FGSM and is inspired by <a href="https://arxiv.org/abs/1907.11932">https://arxiv.org/abs/1907.11932</a> and <a href="https://www.aclweb.org/anthology/P19-1103/">https://www.aclweb.org/anthology/P19-1103/</a>. While the underlying idea behind the algorithm is not novel, the implementation is

The key differences between the algorithms mentioned in the papers and my algorithm lie in the similar word's selection and substitution strategy.

- These papers use a synonym-based word similarity. The problem with this approach is that not all words have synonyms. My algorithm does not choose similar words based on synonyms. I am using pre-trained fasttext embeddings. This allows to find similar words for words without synonyms, misspelled words, concatenation of words.
- My algorithm alters only one word of the original review. Altering only one word especially in a long review makes it
  hard for humans to recognize the adversary reviews.
- Multiple layers of checks are put in to maintain review context similarity of 70% between the original and the adversarial reviews.

# **RESULTS**

**NOTE:** Adversarial reviews are generated from reviews that were correctly predicted by the target model.

## **CMU MOSI**

Original Reviews	Adversarial Reviews	Original Prediction	Prediction After Attack
i mean the blood is like	i mean the blood is like	Positive	Negative
twilight with some scifi with	twilight with some scifi with		
some action and with likable	some action and with		
characters and that that is	lovable characters and that		
important guys	that is important guys		
it was not a <b>real</b> huge saw	it was not a <b>great</b> huge saw	Negative	Positive
twist moment	twist moment		
at how much i really did	at how much i really did	Positive	Negative
enjoy it	enjoys it		_
but i feel that the movie	but i feel that the movie	Negative	Positive
wasnt really concerned with	werent really concerned		
being exciting	with being exciting		
i mean corpse bride hes	i mean corpse bride <b>isnt</b>	Positive	Negative
really good in corpse bride	really good in corpse bride		
but i just <b>couldnt</b> find it	but i just <b>couldent</b> find it	Negative	Positive
funny	funny		
the premiere itself was really	the premiere itself was really	Positive	Negative
cool	coolest		
yeap a horrible protagonist	yeap a horrid protagonist	Negative	Positive
um like i said it wasnt big	um like i said it <b>havent</b> big	Negative	Positive
deal	deal		
i <b>really</b> did	i <b>actually</b> did	Positive	Negative
that so what is still a really	that so what is still a really	Positive	Negative
great movie to take your	tremendous movie to take		
whole family to	your whole family to		
and and we kind of wanted it	and and we kind of wanted it	Positive	Negative
to be like but exept not that	to be like but exept not that		
obvoious but that wouldve	obvoious but that wouldve		
been <b>good</b> right like coz that	been <b>goood</b> right like coz		
it would give tham a reason	that it would give tham a		
coz they wanted to get	reason coz they wanted to		
married but they couldno	get married but they couldno		
because she was gonna	because she was gonna		
marry the other guy	marry the other guy		
i will even pick up this	i will even picking up this	Positive	Negative
movie on bluray	movie on bluray		

# TWITTER SENTIMENT DATASET

Original Tweets	Adversarial Tweets	Original Prediction	Prediction After Attack
is up and getting <b>ready</b> for	is up and getting <b>finished</b> for	Negative	Positive
work	work		
i think that it cell phone had	i think that it cell phone had	Positive	Negative
language options like on a	language options like on a		
computer that would just be	computer that would just be		
amazing xmx	jaw-dropping xmx		
awww thanks i am a regular	awww sorry i am a regular	Positive	Negative
to your site aswell	to your site aswell		

dead battery right in the middle of an alexisonfire	doornail battery right in the middle of an alexisonfire	Negative	Positive
song	song		
aww my sister needs tech support from college at 1 11am good thing big brother that s me is in the ha s sucks for anyone w o sibling	cute. my sister needs tech support from college at 1 11am good thing big brother that s me is in the ha s sucks for anyone w o sibling	Negative	Positive
yesss it was awesome	yesss it was mind-blowing	Positive	Negative
meeting u yesterday	meeting u yesterday		
mb wish i was in town	mb <b>prefer</b> i was in town	Negative	Positive