# Muse-CAR ASTE dataset

# Highlights

- A new benchmark dataset for Aspect Sentiment Triplet Extraction.
- First Aspect Sentiment Triplet Extraction (ASTE) Dataset in Automotive Domain.
- Largest ASTE Dataset to date with annotations for over 28,295 sentences.
- Dataset includes complex aspects not verbatim present in the sentence.
- Domain: Aspect-based sentiment analysis, ASTE, Opinion Mining, Recommender System.

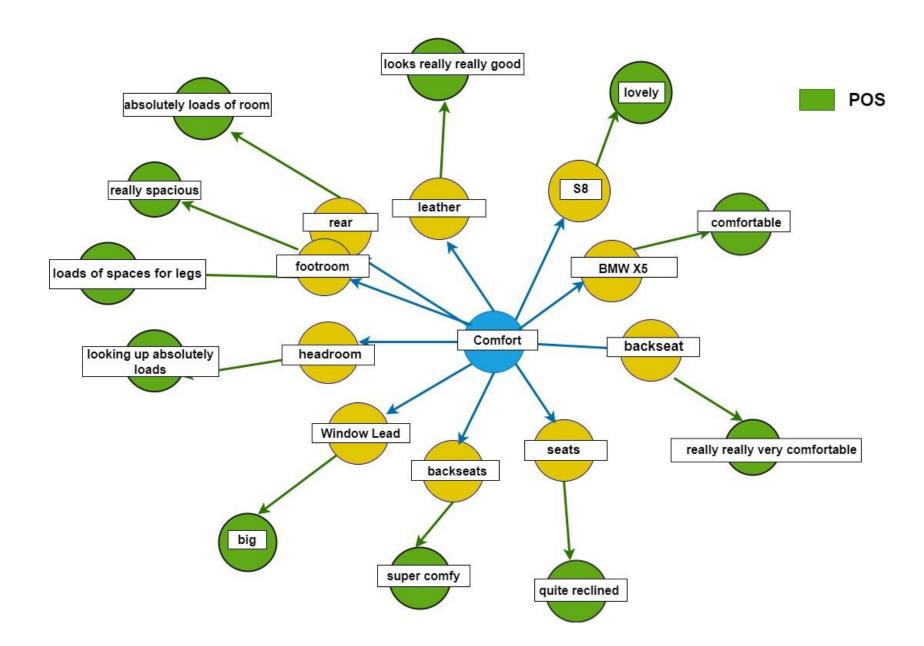
# **Aspect Sentiment Triplet Extraction**

```
The gearbox is rubbish ... steering feels light

(gearbox, rubbish, NEG)
steering, light, POS
```

# **Challenges:**

- i)learning the association between aspect target extraction, and opinion target extraction,
- ii) learning the complex relationship between aspects and opinions
  - one-to-many, many-to-one, overlapped, and embedded,
- iii) extracting multiple sentiments, aspects, and opinions in a single sentence,
- iv) extracting multiword aspects and opinions,
- v) handling vague natural language and extract aspects not directly verbatim



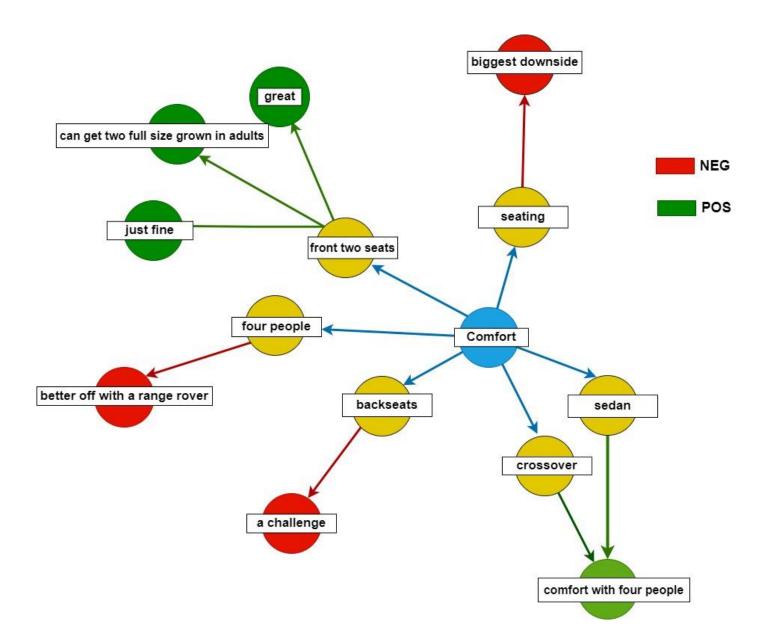


Table 2: Dataset Characteristics

Table 2. Da	taset Characteristics
Characteristic	#Number
Segments	5.5k
Sentences	28,295 ~30k (x5 size
	benchmark)
Topics	10
Non-empty triples	9764~ <mark>10k</mark>
Total Triples	15609~15.6k
Empty Segments	1442
Total Aspects annotated	14168
Total Opinion Annotated	14168
Unique Aspects	3048∼ <mark>3k</mark>
Unique Opinions	7875 ∼ <mark>7.8k</mark>
No. of Videos	303
No. of hours	6 hours
Vocab Size	13,138 (6k benchmark)
Implicit Aspects	2435 (0 benchmark)
Implicit Triples	3385 (0 benchmark)
Implicit Opinions	1403 (0 benchmark)
Max. Text Length	14280
Avg. Words	113.50 (longer transcripts
per segment	16.43 benchmark)
Domain	Automotive (first)
Multiword Opinions	8688~ <mark>8.6k</mark>
Multiword Aspects	4912~5 <mark>k</mark>
Multiword Triples	10,603~10.6k (5k benchmark)

ble 3: Dataset sizes and class distribution over training and validation

DATA	Total Triples	Segments	Empty Triples / Segments	Non- Empty Triples	Positive	Negative	Neutral
Training	~11.3k	~4.2k	1206	10104	1793	10104	1792
_	(112310)	(76%)	(10.7%)	(89.3%)	(64.5%)	(17.8%)	(17.7%)
Development	~4k	~1.3k	236	4063	2813	469	781
_	(4299)	(24%)	(5.5%)	(94.5%)	(69.4%)	(11.6%)	(19%)

Table 4: Dataset Columns and their description (\* From the Original Dataset)

Variable	Description
Name	
Unnamed:0	The first column is unnamed and the index.
id*	It is the video id
segment_id*	Each video transcript is divided into segments. It is the segment id
label_topic*	Ranges from 0 to 10 and represents the topic class the segment corresponds to.
text*	It is the transcript text for that segment
aspect	It is aspect extracted from the segment, each row corresponds to exactly one aspect, and
	multiple aspects are mentioned in sub- sequent rows for each segment
opinion	It is opinion extracted from the segment, each row corresponds to exactly one aspect,
	and multiple aspects are mentioned in sub- sequent rows for each segment
sentiment	It refers to the sentiment polarity for each aspect/opinion pair. It is a categorical column
-	with 3 possible values (pos, neu, neg) for positive, negative, and neutral sentiment

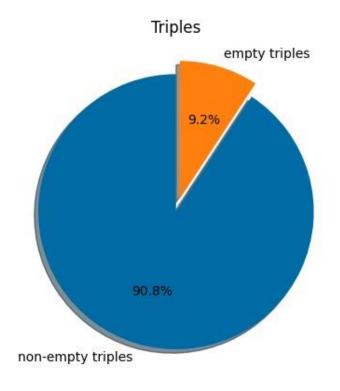
Table 5: Examples

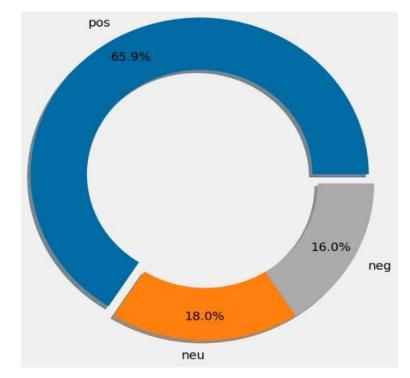
review text	aspect	opinion	sentiment	remarks
So too, with the fact that you	rear	1	D	Normal
got some huge rear windows on this, so smaller people can see.	windows	huge smaller people	Pos	Aspect (not
	visibility	can see	Pos	verbatim)
	feel	like sports car	Pos	Normal
Feels like a sports car. It looks	1001	ince sports car	1 05	Opinion (not
like one	look	like sports car	Pos	verbatim)
		frankly does		
Stagring frontly does not		not communicate		Normal
Steering, frankly, does not communicate very well.	steering	well	Neg	
Steering Wait is okay once you	steering		$\mathcal{C}$	Spelling mistakes
set it up.	weight	okay	Neu	in transcripts

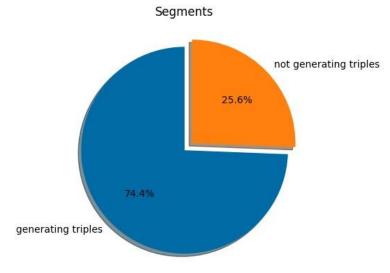
# **Data Distribution**

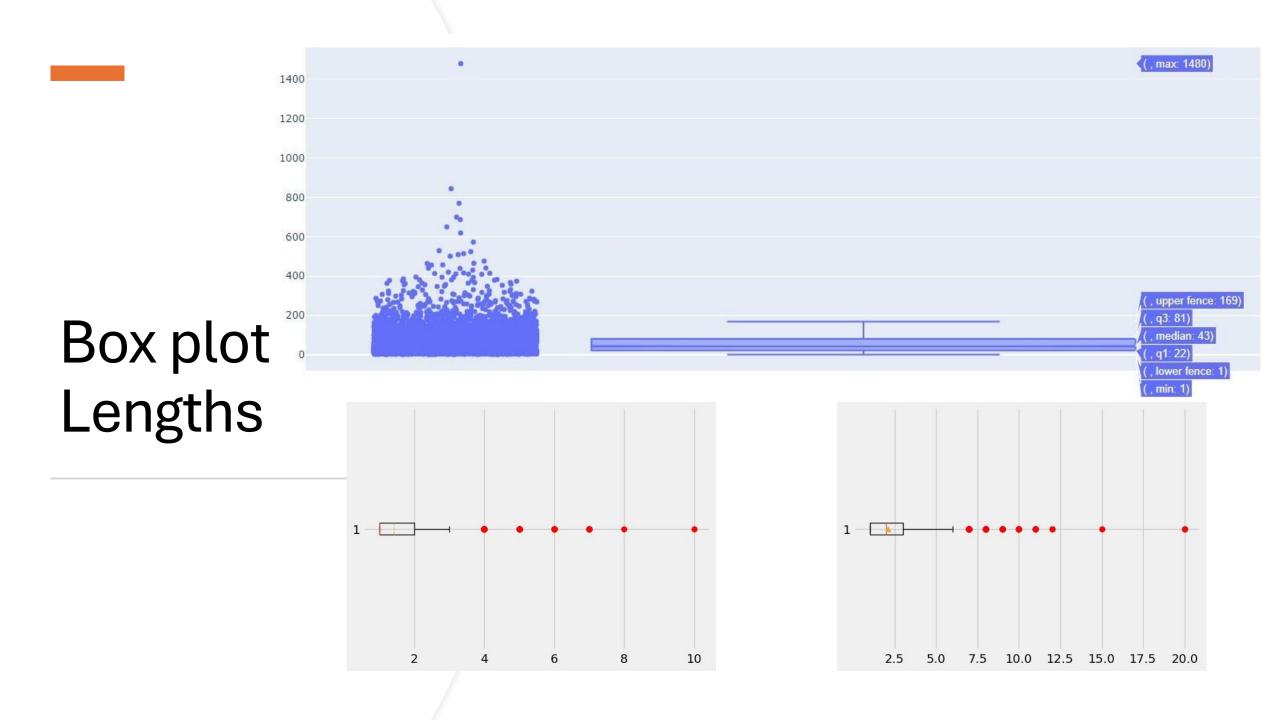
 Table 6: Final Data Distribution on Sentiment

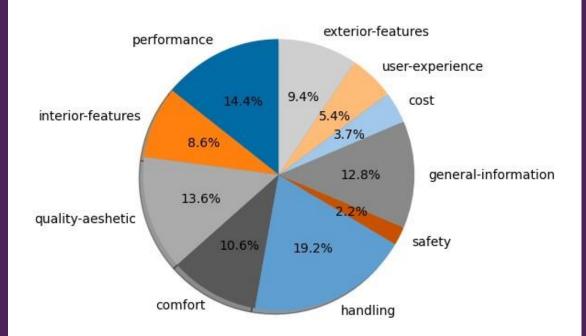
Sentiment Class	pos	neg	neu
Total Data	9332	2262	2573

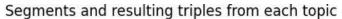


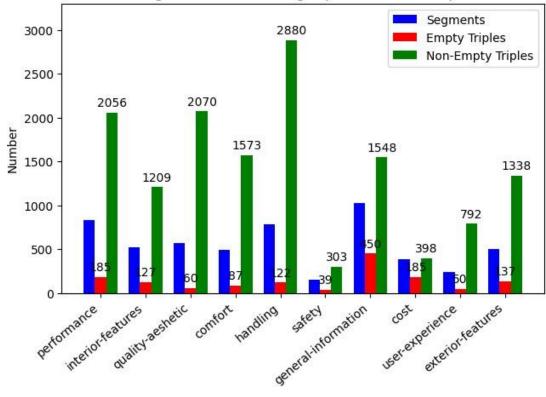




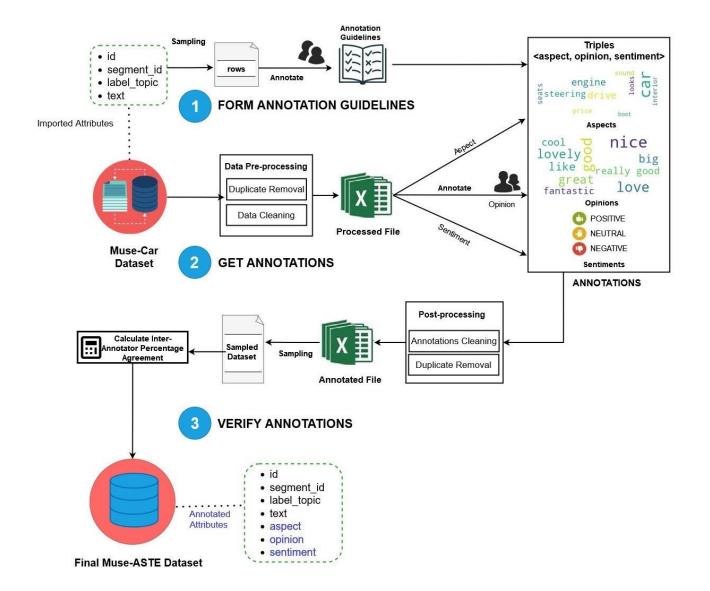












### **Algorithm 1** Sampling Protocol

```
1: Topic Count=[ ]
2: for each topic 0 \rightarrow 10 do
       procedure GetCount(topic,dataset)
          Subset=dataset where label_topic== topic
          Count \leftarrow No. of Samples in Subset
          Topic Count[topic]← Count
 6:
          return Topic Count
 7:
      end procedure
9: end for
10: Sample Count=[ ]
11: procedure MaxSampleCount(Topic Count, dataset)
      for each value in Topic Count, i \leftarrow 0 to 10 do
          Sample Size= \leftarrow 0.1 * value
13:
          Sample Count[i]← Sample Size
14:
15: end for
      return Sample Count
17: end procedure
18: procedure SAMPLE (Sample Count, dataset)
      for each topic 0 \rightarrow 10 do
          Size ← Sample Count[topic]
20:
          Subset=dataset where label topic== topic
21:
          Sampled Subset ← Randomly sample Size from the Subset
22:
          Annotator File ← Annotator File + Sampled Subset.
23:
      end for
24:
      return Annotator File
26: end procedure
27: procedure SHUFFLE
28: end procedure
```

# **Annotator Feedback**

nent_i lab	el_to	text						triplet		aspect	opinion	sentiment		
12	9	Parking? Yes.	Remote control pa	rking connected t	o the car . See if I	can do it . It's tal	king to the car. Can see	e that . (parking,	, remote	e control , pos)	modified/short	ened		
								(commu	nication	n, it's talking to the	fine			
								(visibility	, can s	ee that, pos)	not needed			
20	3	It comes in at 3	5.2 inches , so it's	a little bit tight from	m my six foot self,	but still comforta	able nonetheless.	(height,	35.2 in	ches, neu)	objective			
								(space, a	a little b	oit tight, neg)	correct			
										omfortable, pos)	correct			
5	0	Now this car co	mes in two variation	ons . The 3 28 and	the 3 35 The diffe	rence is that und	der the 3 35 hood or bon	inet is A3 lea <mark>(car-vari</mark> a	ations,	two, neu)	correct just sh	ortened		
								(3 35 en	gine, A	3 leader 300D hors	not needed/ob	jective		
								(3 28 an	d 3 35,	quick, pos)	(engines, quick,	pos)	modified	
								( <del>3 28 an</del>	<del>d 3 35</del> ,	fast, pos)	(engines, fast,p	os)	modified	
								(location	, ameri	ca, neu)	not needed/ob	jective		
								(transmis	ssion ir	America, eight sp	not needed/ob	jective		
								(transmis	ssion ir	n Europe, six speed	not needed/ob	jective		
2	0	Now I've got 54	miles of charge .	t's not full . It's ab	out half empty on			(charge,	54 mile	es, pos)	not needed/ob	jective		
								(charge,	not full	l, neg)	correct			
								(charge,	about	half empty, neg)	correct			
16	4	It's possible . It'	s comfortable . It's	fun to drive .				(drive, fu	in, pos)		correct			
								(car seat	s, com	fortable, pos)	(drive, comforta	ble, pos)	modified	
											(drive, possible,	neu)	added	
12	4	After that , I gue	ess you're on your	own .				-			correct			
25	7	That package a	dds an additional	\$750 if you wante	d it , but make you	r way to the front	t seats .	(package	e, adds	an additional \$750	not needed/ob	jective		
								(front sea	ats, ma	ike your way to, ne	not needed/ob	jective		
32	6	So then overall	, what I think this E	BMW X5 was quit	e interesting.			(BMW X	5, quite	e interesting, pos)	correct			
16	7	Whitefield A3 B	alsa wood Phil bei	ng with him . S8 b	ones . It's upto of	a point yesterday	and finds out tell you a	bout which o -			correct			
14	1	It makes no diff	erence now . This	is a two plus two				_			correct			
6	2	Unlike in previo	ous generations, th	at's now so much	more to the A8 in	the way it looks		(A8, mor	e in the	e way it looks, pos)	(looks, so much	more, pos)	modified/shorte	ned
5	3	Still , standard	equipment is very	good , and the ma	ssage seats are in	cluded A standa	rd, though, to be hones	st , massive s <mark> (equipm</mark> e	ent, ver	ry good, pos)	correct			
								(massag	e seats	s, included, pos)	(seats, massage	e, pos)	modified/shorter	ned
								(seating,	massi	ve, <del>neg</del> )	(seating, massiv	ve, pos)	check sentiment	t
								(features	, inclu	des panoramic sun	roof, pos)	think it is talkir	ng about the other	car that inclu
9	0	Think a little pa	rt of the universe h	ad begun to end l	because , you kno	w, it's still got 35	5 BHP two litre turbo en	gine under ti (engine.	355 BI	HP two litre turbo, p	objective/not n	needed	_	
				_		_		(bonnet,	very u	gly, neg)		break into two	triples of two opin	nions (bonnet,
										high, neg)				. ,

# **Annotation Guidelines**

- extract all aspects for the segment one triplet per row
- split multiple opinions into triplets like "drive nice and fun -> (drive, nice, pos), (drive, fun, pos)
- do not extract unrelated subjective/objective information not talking about the entity line "enjoyed the video" should result in <-,-,->
- implicit aspects are extracted. "car is low to the ground"-> (height, low, neu)
- use the same text as present in the original review segment
- shorten it as much as possible
- vi) use common sense from the customer point of view for marking correct sentiment like high price is negative, or having a large boot is the car is positive, small windows is negative because visibility will be less
- vii) i spelling errors in the text transcripts, correct them and extract

## **Algorithm 2** Annotation Protocol

- 1: Start.
- 2: Select skilled annotator(s).
- 3: Generate automatic raw labels using the existing triplet generation technique (SPAN-ASTE (Xu et al., 2021)) trained on ASTEV2 16 res restraint weights) to begin with.
- 4: Sample 100 rows.
- 5: **procedure** Preprocessing (Dataset)
- 6: Duplicate removal and Data cleaning.

## 7: end procedure

- 8: Annotate the entire dataset.
- 9: **while** Agreement  $\leq$  threshold **do**
- 10: **procedure** Postprocessing (Annotations)
- 11: Duplicate removal, Stop-word Removal, Lemmatization
- 12: end procedure
- 13: **procedure** calAgreement (Annotations) **for** triples and segments **do**Number of agreements = Count of annotations that match between annotators above a similarity threshold
- 14: Percentage agreement=(Number of agreements/Total number of annotations)\*100
- 15: end for
- 16: **end procedure**

Revise the guidelines, provide additional instructions and increase the sample by adding more rows from the subset.

- 17: end while
- 18: Compare and analyze the annotations for acceptability.

# Inter-Annotator-Agreement

TPA = 
$$\frac{No. \ of \ agreeing \ triples > \tau}{Total \ No. \ of \ triples \ in \ the \ dataset} * 100(1)$$

$$SGA_{Class} = \frac{No. \ of \ agreeing \ segments > \tau}{Total \ No. \ of \ segment \ in \ the \ dataset} * 100$$
 (2)

**Table 7:** Simple Triple-Wise Percentage Agreement between annotators.

Similarity Threshold τ	Triple Percentage Agreement	<b>Aspect Opinion Pair Agreement</b>					
·	0/0	0/0					
0.60	79.74138	79.74138					
0.65	<u>73.41954</u>	<u>74.28161</u>					
0.70	67.52874	67.81609					
Sentiment Agreement Percentage in Triples: 73.069							

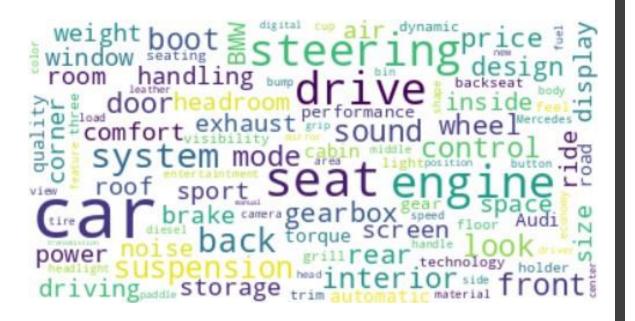
**Table 8:** Segment-Wise TPA analysis at different similarity thresholds

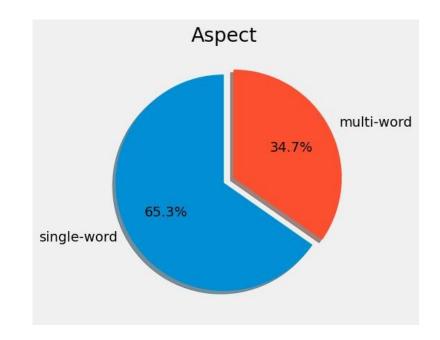
imilarity Threshold for Triples	Intra-Segment Triple-Wise Agreement Percentage (TPA)	SGA
65	>=0.6	72.13115
6	>=0.65	70.4918
6	>=0.6	73.77049
ombined Average TPA for all seg	ments (at $\tau$ = 0.6):72.2405	

**Table 9:** Intra-Class, Intra-Segment Group Agreement analysis at different similarity thresholds.

Similarity	Triple SGA	<b>Aspect Opinion Pair</b>	Aspect	<b>Opinion</b>	Sentiment	
Threshold		SGA	SGA	SGA	Class	
0.60	80.32787	80.32787	76.22951	77.04918	Average:	
0.65	80.32787	80.32787	74.59016	72.95082		
0.70	77.86885	78.68852	72.95082	69.67213	<b>72.13%</b>	







<b>Table 11</b> Top-k most frequently annotated opinions per sentiment class in the	dataset $(k=15)$ .
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<b>Sentiment Class</b>	Words {word: frequency}
Positive	<pre>{'nice': 171, 'good': 136, 'love': 120, 'lovely': 91, 'great': 87, 'like': 87, 'big': 76, 'really good': 64, 'better': 52, 'brilliant': 52, 'pretty good': 51, 'heated': 50, 'fantastic': 49, 'amazing': 46, 'really nice': 44}</pre>
Negative	<pre>{'annoying': 35, 'little': 26, 'fake': 22, 'problem': 20, 'not great': 19, 'small': 15, 'not like': 11, 'cheap': 8, 'little bit': 8, 'none': 8, 'shame': 8, 'smaller': 8, 'lot of money': 7, 'heavy': 6, 'not so great': 6}</pre>
Neutral	<pre>{'all wheel': 53, 'big': 41, 'little': 35, 'standard': 34, 'electric': 22, 'four wheel': 20, 'small': 19, 'all right': 18, 'automatic': 18, 'heavy': 18, 'okay': 18, 'decent': 17, 'SUV': 15, 'lower': 15, 'not bad': 15}</pre>

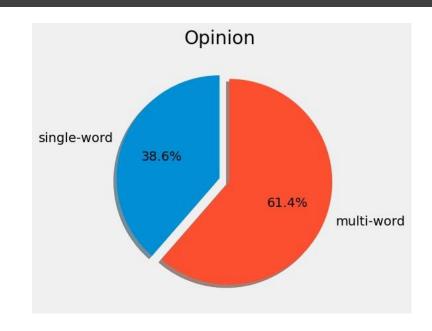


Table13: Properties of our dataset where #W/S, denotes the average number of words per review segment, #MA,#MO, #MT denotes number of multi-word aspects, opinion, and triples, #IA, #IO, #IT denote the number of implicit aspects, opinions and triples, #T/S denotes the average no. of triples per segment, and #T/NS denotes the average no. of triple per non-empty segment (segments yielding triples), #W/T, #W/AO denotes the average number of words per triple and aspect opinion pair, and #Vocab is the vocab size.

#W/S	#MA	#MO	#MT	#IA	#IO	#IT	#T/S	#T/NS	#W/T	#W/AO	#Vocab
113.50	4912	8688	10,603	2435	1403	3385	2.566509	3.47145	4.524697	3.524696	13138

Table 12: Comparison of Muse-CarASTE with benchmark datasets.

Contributions	Muse-CarASTE	<b>ASTE-v2</b> [5]	Original Muse-Car	
			[1]	
<b>ASTE- labels</b>	Yes	Yes	No	
<b>Topic labels</b>	Yes	No	Yes	
Domain	Automotive Vehicles	Hotels & Laptop	Automotive Vehicles ~30k sentences /	
	~30k sentences /	~6k sentences (5,989)		
Scale	~5.5k segments		~5.5k segments	
Complexity –	Long Video Transcripts	Short text review	Long Video	
Length/Data Type			Transcripts Not Applicable	
<del>-</del>	Contains Implicit Aspects	No Implicit Aspect and		
<b>Complexity - Labels</b>	and opinion terms	Opinion Terms		

# Baseline Models

# Generative-ABSA. (Zhang et al., 2021)

generation-based framework

extraction paradigm [(triple<sub>1</sub>); (triple<sub>2</sub>) ...; (triple  $_k$ )], where k=no. of triples the segment generates.

triple consists of (aspect a, opinion o, sentiment p).

final target representation for each segment is  $[(a_1, o_1, s_1); (a_2, o_2, s_2), \ldots; (a_k, o_k, s_k)]$ .

fine-tune the pre-trained T5 model (Raffel et al.,2020) on our dataset.

## **BMRC**

The model (Chen et al., 2021) uses machine comprehension

BERT for encoding.

two binary classifiers: aspect-oriented, and opinion-oriented to identify these spans, which are then merged to get the result

Sentiment is inferred from the CLS token.

## **BART-ABSA**

(Yan et al., 2021) is a pointer-based generation method generates indices of aspect term, opinion term and classifier.

## **SPAN-ASTE**

tagging-based method predicting whole spans of targets and opinions. (Xu et al., 2021)

# Results

able 14: Detailed Result of baseline model (Zhang et al., 2021) on our dataset using precision, recall, and F1 measures up to 4 decimal places on dev file of whole dataset corresponding to the original MuSe-Car dataset (Stappen et al., 2021a, 2021b).

	precision	recall	<b>F</b> 1
Aspect	0.7143	0.7196	0.7169
Aspect-Sentiment Pair	0.7611	0.7667	0.7639
Opinion	0.9126	0.9193	0.9156
Aspect-Opinion Pair	0.9272	0.9341	0.9306
Triple	0.9300	0.9232	0.9266

# Results-processed Dataset

: Detailed Result of BMRC (Chen et al., 2021) baseline model on our dataset

	Precision	recall	F1
Aspect	0.856	0.726	0.786
Aspect-Sentiment Pair	0.721	0.611	0.761
Opinion	0.802	0.707	0.751
Aspect-Opinion Pair	0.692	0.626	0.757
Triple	0.599	0.540	0.568

Table 16: Detailed Result of baseline model Generative-ABSA (Zhang et al., 2021) on our dataset using precision, recall, and F1 measures up to 4 decimal places.

	precision	recall	<b>F</b> 1
Aspect	0.3704	0.2701	0.3124
Aspect-Sentiment Pair	0.308	0.2246	0.2598
Opinion	0.4088	0.2981	0.3448
Aspect-Opinion Pair	0.3064	0.2234	0.2584
Triple	0.1884	0.2584	0.2179

Table 17: Detailed Result of BARTABSA (Yan et al., 2021) baseline model on our dataset

	Precision	recall	<b>F1</b>
Aspect	0.445	0.431	0.438
Opinion	0.518	0.516	0.513
Aspect-Sentiment Pair	0.403	0.406	0.488
Aspect-Opinion Pair	0.298	0.283	0.290
Triple	0.256	0.243	0.249

# Comparison with our dataset

Table 18: Result of Span-ASTE (Xu et al., 2021) baseline model on our dataset and SemEval Dataset (xuuuluuu, 2020).

Dataset	Triple Precision	Triple Recall	Triple F1
Muse-ASTE	0.409	0.171	0.241
14lap	0.634	0.558	0.594
14res	0.729	0.709	0.718
15res	0.622	0.644	0.632
16res	0.694	0.712	0.702

Table 19: Results of baseline models on SemEval Datasets (xuuuluuu, 2020) and our Dataset using F1 scores.

Model	Dataset	Aspect	Opinion	Aspect	Aspect	Triple
		(F1)	(F1)	Opinion	Sentiment	(F1)
				Pair	Pair (F1)	
				(F1)		
Generative-	14 lap	0.63	0.61	0.52	0.48	0.43
ABSA	14 res	0.66	0.71	0.69	0.63	0.65
(Zhang et	15res	0.66	0.71	0.60	0.61	0.56
al., 2021)	16res	0.67	0.75	0.67	0.62	0.63
	Muse-	0.31	0.34	0.26	0.26	0.218
	ASTE					
BMRC	14 lap	0.76	0.73	0.67	0.66	0.59
(Chen et	14 res	0.82	0.84	0.76	0.76	0.71
al., 2021)	15res	0.72	0.78	0.66	0.658	0.61
	16res	0.82	0.83	0.76	0.73	0.68
	Muse-	0.786	0.751	0.757	0.761	0.568
	ASTE					
BART-	14 lap	0.79	0.84	0.68	0.69	0.60
ABSA	14 res	0.85	0.84	0.75	0.78	0.71
(Yan et al.,	15res	0.78	0.61	0.56	0.54	0.50
2021)	16res	0.85	0.84	0.75	0.76	0.68
	Muse-	0.438	0.513	0.290	0.404	0.249
	ASTE					



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# <u>GitHub - AtiUsm/MuseASTE: Aspect Sentiment Triplet Extraction Annotations for the MuSe-Car Dataset</u>

