

Balancing between Holistic and Cumulative Sentiment Classification

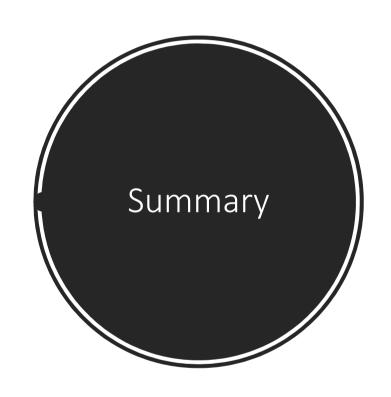
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Extends: A Hybrid Deep Learning Network for Modelling Opinionated Content







CUMULATIVE VS HOLISTIC SENTIMENT ASSIGNMENT



MODEL ARCHITECTURE



COMPONENT'S ANALYSIS

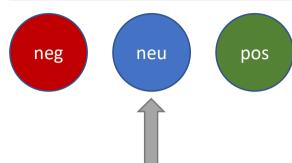


EXPERIMENTAL EVALUATION

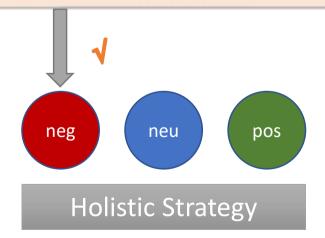


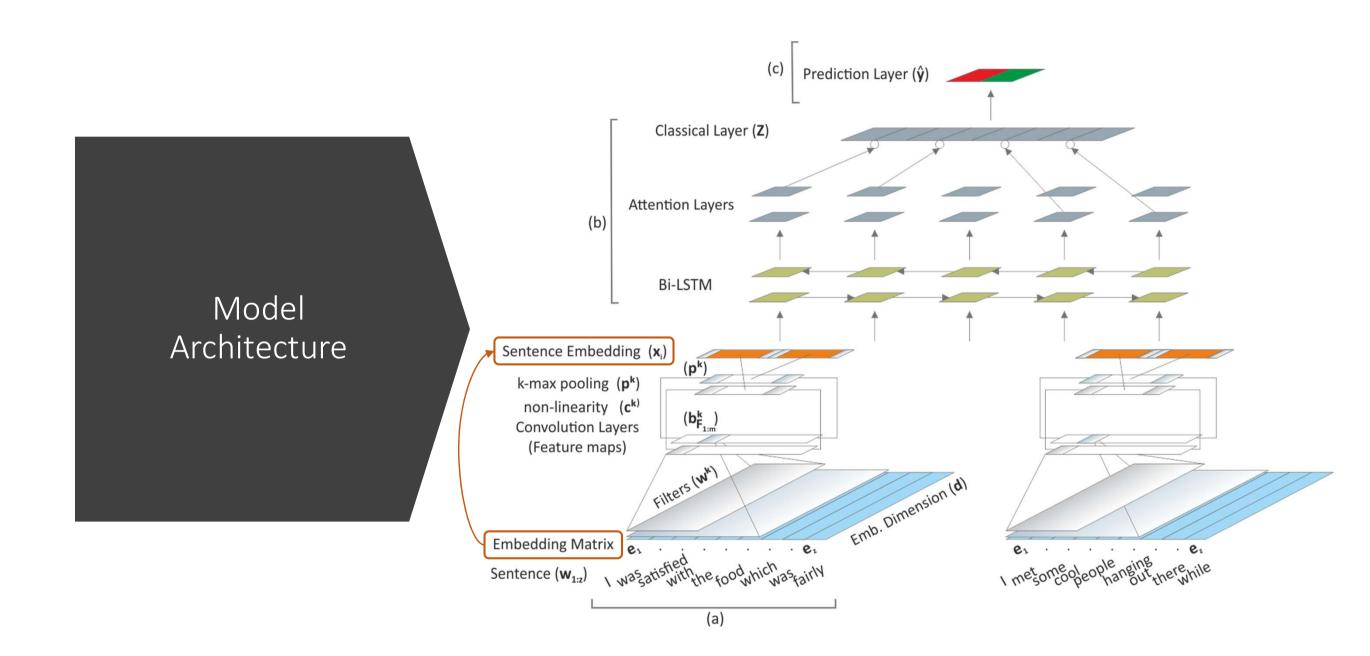
CONCLUSION

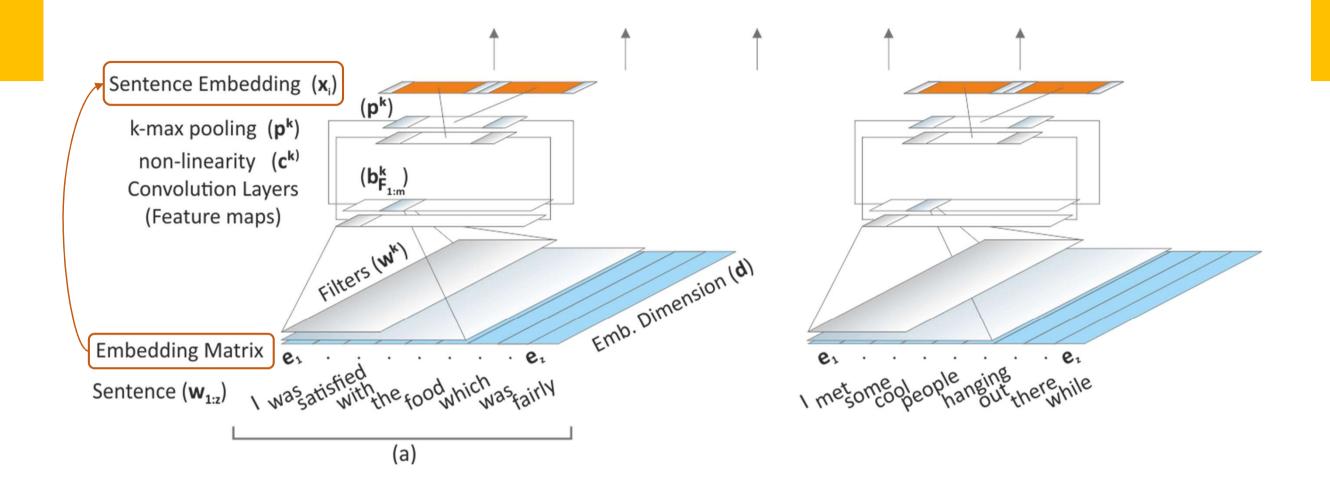




Cumulative vs Holistic Sentiment Assignment "The location is excellent (+). The food is mediocre, and milder than they advertise (-). The wait staff is polite and bland (+). At several opportunities, they were missing for more than 5 mins (\pm) . The bill will be higher than anyone expects (-)."







Exploring Sentiment Patterns

Vector Element $b_i^k = w^k \cdot e_{i:i+h-1}$	(1)	Feature Map Vector (length Z) $b_{F_i}^k = [b_1^k; \cdots; b_i^k; \cdots; b_z^k]$	(2)
Array of Feature Map Vectors $b^k_{F_{1:m}} = [b^k_{F_1}; \cdots; b^k_{F_i} \cdots; b^k_{F_m}]$	(3)	Non-Linearity $c^k = f^{nl}\left(b_{F_{1:m}}^k,eta^k ight)$	(4)
$p^k = k \text{-}max[c^k]$	(5)	Sentence Embedding $x_i = [p^1; \cdots; p^k]$	(6)

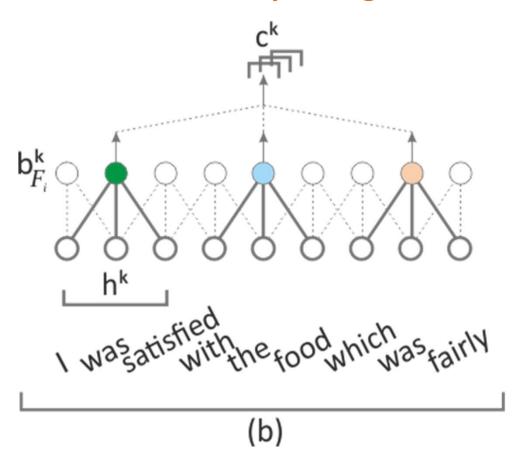
single-max pooling VS k-max pooling in a Convolution Layer

Single max-pooling

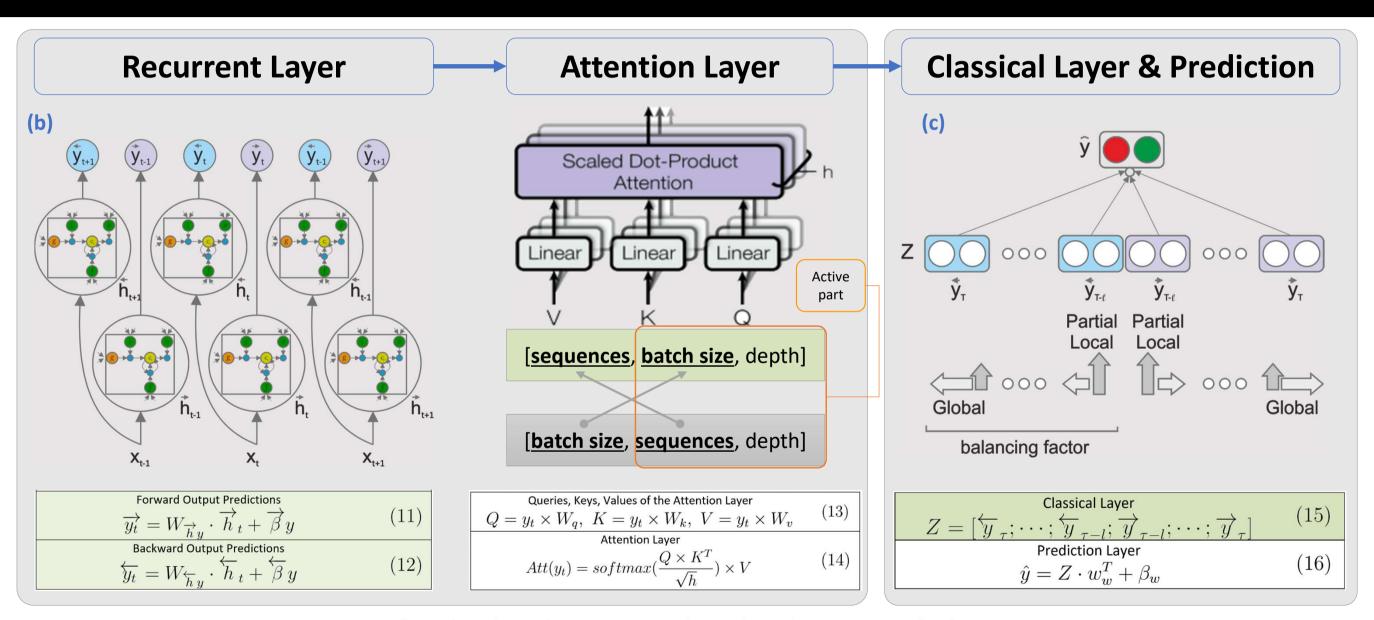
wasatisfied with the food which was fairly

(a)

K-max-pooling



Encoding Opinion – Augmenting Features – Grasping Sentiment Assignment Strategy



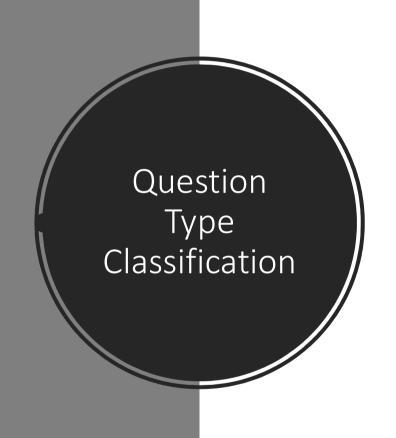
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Balancing Factor and Sentiment Assigning Strategy

Cumulative Strategy Holistic Strategy Local Local Local Local Global Global Global Global balancing factor = 0 balancing factor = 1

		SUBJ	YELP-bin	SEMEVAL	SST-bin	MR	YELP	SST
	HolCmax	94.80%	91.16%	84.96%	86.27%	84.01%	52.75%	49.28%
	HolC	94.11%	90.00%	84.64%	85.48%	79.78%	50.75%	48.62%
HolC can better	HolC w/o Att	93.54%	89.54%	84.10%	84.51%	79.69%	49.46%	47.52%
grasp sentiment	CNN-static (*)	50.51%	77.82%	71.23%	83.51%	78.30%	31.19%	43.28%
Fluctuations	BLSTM (*)	49.87%	75. <mark>5</mark> 7%	70.19%	84.34%	77.48%	31.03%	43.52%
	BiLSTM-Max	92.40%		-	84.60%	81.10%		-
	DAN				86 30%	_		47.70%
	DCNN	-	-	-	86.80%	-	-	48.50%
	CNN	93.40%	-	-	87.20%	81.50%	-	48.00%
Attention,	RecNTN	-	-	-	85.40%	-	-	45.70%
improved the	CT-LSTM	-	-	-	88.00%	-	-	51.00%
generalization in	C-LSTM	-	-	-	87.80%	-	-	49.20%
all benchmark	SWEM-concat	93.00%	-	-	84.30%	78.20%	-	46.10%
datasets	RNN-Capsule	-	-	-	-	83.80%	-	49.30%
datasets	MEAN	-	-	-	-	84.50%	-	51.40%
	AdaSent	95.50%	-	-	-	83.10%	-	-
	USE	93.90%	-	-	87.21%	81.59%	-	-
	Fast Dropout	93.60%	-	-	-	-	-	-
	SDAE	90.80%	-	-	-	74.60%	-	-
	GRU-RNN	91.85%	-	-	-	78.26%	-	45.02%
	Capsule-B	93.80%	-	-	86.80%	82.30%	-	-
	Emo2Vec	-	-	-	82.30%	-	-	43.60%
Sentiment	BiLSTM-CRF & CNN	-	-	-	88.30%	82.30%	-	48.50%
Classification	SwissCheese	-	-	82.00%	-	-	-	-
Classification	CUFE	-	-	83.40%	-	-	-	-
	ECNU	-	-	84.30%	-	-	-	-
	UNIMELB	-	-	87.00%	-	-	-	-
	Thecerealkiller	-	-	82.30%	-	-	-	-
	TwiSE	-	-	82.60%	-	-	-	-
	Finki	-	-	84.80%	-	-	-	-

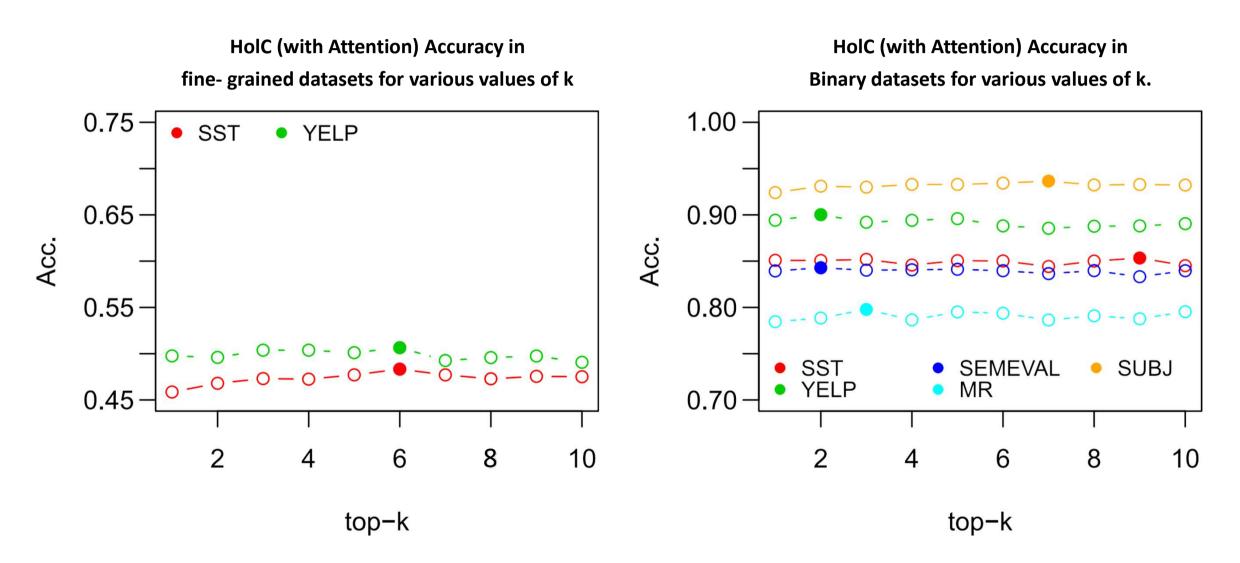
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TREC dataset

	Acc	Best Acc
HolC	<u>98.64%</u>	99.00%
HolC w/o Att	98.48%	98.80%
CNN-static (*)	98.60%	98.80%
BLSTM (*)	97.84%	98.80%
CNN	93.60%	-
AdaSent	92.40%	-
BiLSTM-Max	88.20%	-
DCNN	93.00%	-
USE	98.07%	-
SDAE	78.40%	-
GRU-RNN	93.00%	-
Capsule-B	92.80%	-
SWEM-aver	92.20%	-

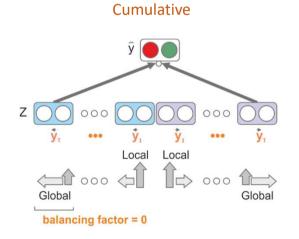
The Contribution of the k-max Pooling Operation

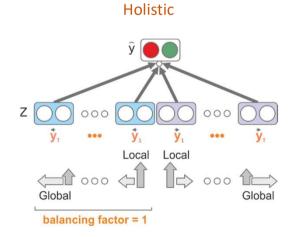


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$\overline{ m BF}$	SUBJ	YELP-bin	SEMEVAL	SST-bin	MR	YELP	SST	TREC
0	94.11%	89.67%	84.64%	85.48%	79.78%	50.75%	48.62%	98.60%
0.25	93.38%	89.66%	84.09%	84.95%	79.47%	50.19%	47.13%	98.44%
0.5	92.23%	89.80%	84.28%	84.63%	79.03%	49.16%	47.65%	98.52%
0.75	93.28%	89.52%	84.19%	85.10%	78.73%	$\underline{50.65\%}$	47.78%	98.64%
1.00	93.50%	$\boldsymbol{90.00\%}$	84.31%	84.96%	79.22%	49.85%	47.04%	98.60%

Holistic/Cumulative content identification over a set of different datasets & balancing factor (BF)





Conclusion

Novelties of the Proposed Method

The introduction of a sentence embedding via a Convolution Neural Network (1) A bi-directional recurrent neural network for encoding semantic content sequentially (2) Classical layer that exploits both local and global information (3) A hyperparameter that balances mixed content motifs named **Balancing Factor** (4) An improved convolution operation that better exploits the input information (5) A k-max-pooling operation over the single max-pooling after the convolution layer (6) An improved design of the attention layer capable of improving the

The utilization of pre-trained word vectors over the randomly

generalization task and

initialized ones

(8)

