

Domain-Informed Label Fusion Surpasses LLMs in Free-Living Activity Classification (Student Abstract)

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<https://github.com/shovito66/FUSE-MET>

Motivation

Challenges with labels collected in free-living environments

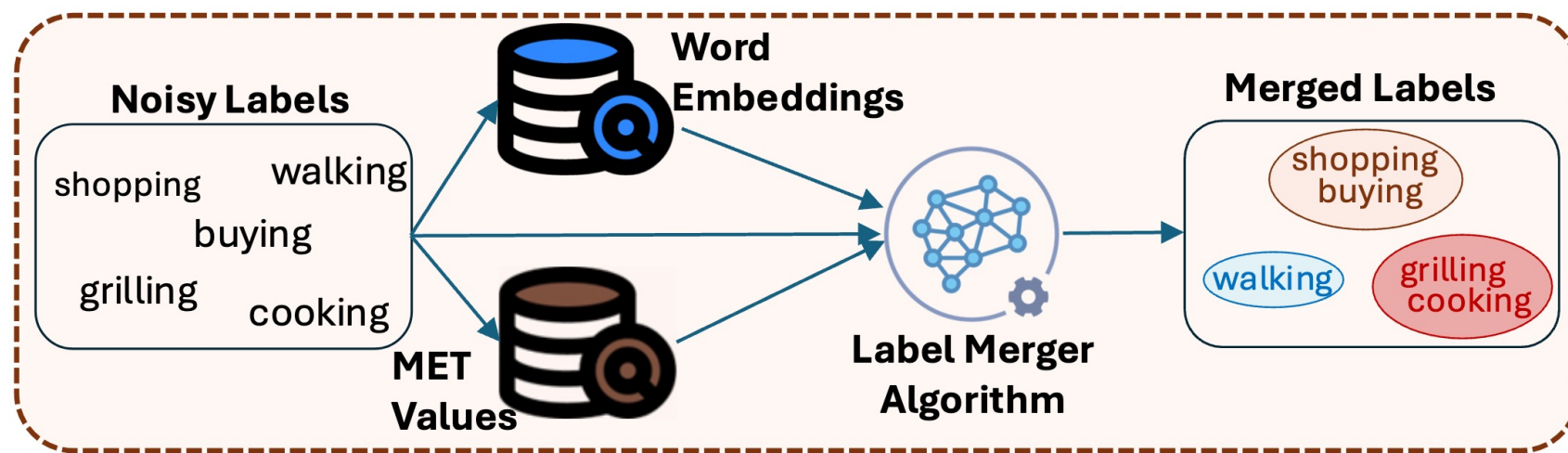
- **Noisy Labels:** Labels provided by participants are inconsistent and subjective.
- **Sparse Data:** Variability in the frequency and intensity of recorded activities.
- **Undefined Activity Vocabularies:** Different terminologies for similar activities

These challenges makes the downstream task (e.g., activity recognition) more difficult.



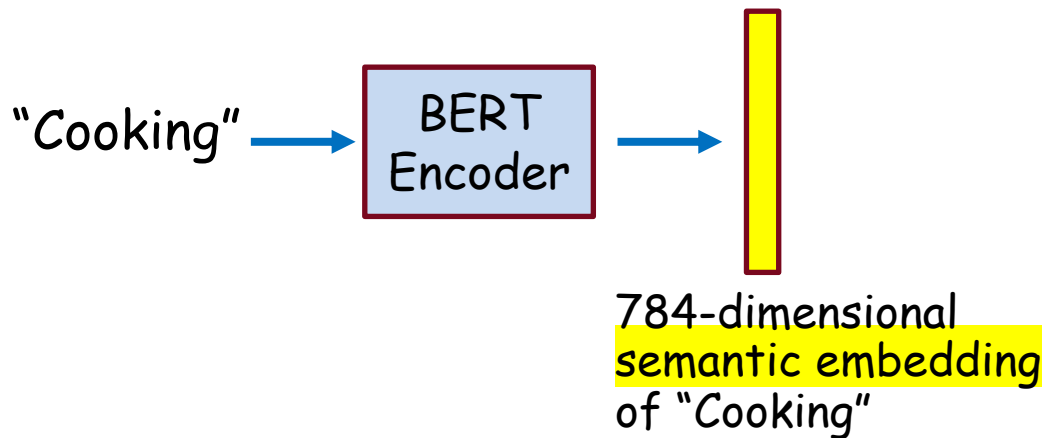
Proposed Framework: FuSE-MET

- Combines semantic embeddings (BERT) with domain-specific Metabolic Equivalent of Task (MET) values.
- Reduces label complexity by merging similar activities.
- Lambda-weighted fusion balances:
 - Semantic similarity
 - Physical intensity



Semantic Embeddings (BERT)

- Pre-trained BERT model captures semantic relationships between activity labels.
- Enables understanding of synonymous and related terms.

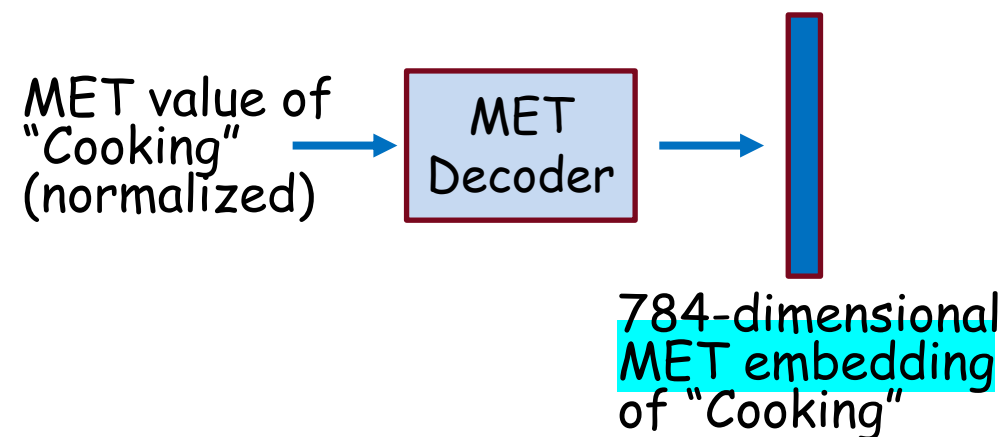
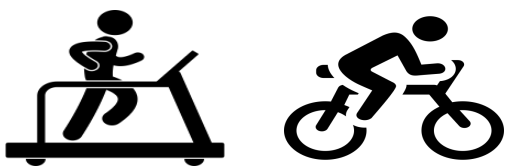


Algorithm 1: FuSE-MET algorithm. $w_a \in \mathbb{R}^d$, $m_a \in \mathbb{R}^d$, $f_a \in \mathbb{R}^d$. a' is the closest label to a in the MET database. $Decoder : \mathbb{R}_+ \rightarrow \mathbb{R}^d$ creates vectors from met values.

- 1: **Input:** Noisy labels L_{user} , #clusters K , domain coefficient λ , BERT embedding model B , MET values M
 - 2: **Output:** clustering labels for L_{merge}
 - 3: **Begin**
 - 4: initialize F as an empty matrix of feature vectors.
 - 5: **for all** label a in L_{user} **do**
 - 6: $w_a = B(a)$, the word vector of a
 - 7: $a' = \operatorname{argmin}_{a''} (\cos_dist(w_a, B(a''))) \quad \forall a'' \in M$
 - 8: $m_a = Decoder(\text{normalized MET value of } a')$
 - 9: $f_a = (1 - \lambda) \times w_a + m_a \times \lambda$
 - 10: add f_a to feature vectors F
 - 11: **end for**
 - 12: **return** $L_{merge} = K$ clusters by doing k -means on F
 - 13: **End**
-

Domain-Specific Knowledge: MET Values

- MET values quantify physical intensity of activities.
- Example MET values:
 - Walking: 2.5
 - Cycling: 8.0
- Helps balance classification based on physical intensity.

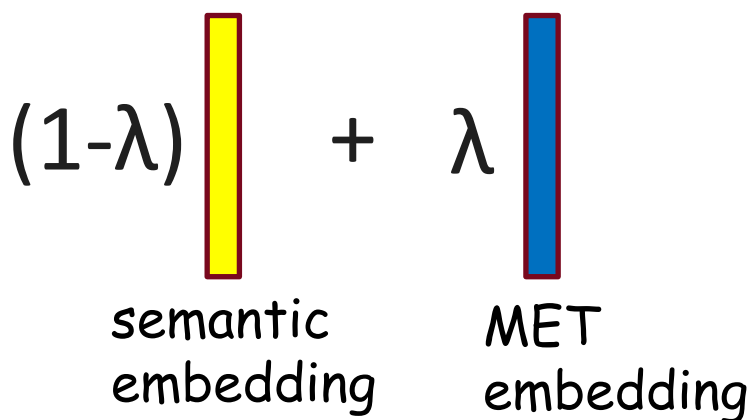


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Lambda-Weighted Fusion

- Fusion of semantic embeddings and MET values: **Weighted combination of BERT embeddings and MET values.**
- Allows **flexible adjustment** to prioritize semantic meaning or physical intensity.



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Unsupervised Clustering

- Group similar labels based on the combined feature vector using k-means clustering

$$\lambda = 0.5, k = 5$$

Bathe, Eat, Getting Hair Cut, Meeting, Napping, Pray ROSARY, Read, Relax, Sleep, Take Medicine, Test, Watch TV, Websurf, Work

Beach, Church, Church Services, Garden, Travel

Computer, Computer Work

Cycle

Clean, Cook, Dog Walk, Dress, Drive, Driving, Exercise, Laundry, Play, Run, Shop, Shopping, Socialize, Walk

Evaluation

Study Context:

- Clinical study with patients with cardiovascular disease.
- Data collected from smartphones: accelerometer and gyroscope signals.
- 5-second windows with extracted features (e.g., signal intensity, variance).

Models Evaluated:

- Classifiers: Random Forest, 1-nearest neighbor (1NN), SVM, Fully-connected neural network (NN), XGBoost, DANets, CNN.
- Baselines:
 - GPT-4-based clustering without MET values.
 - Nonfusion model with 36 distinct clusters.

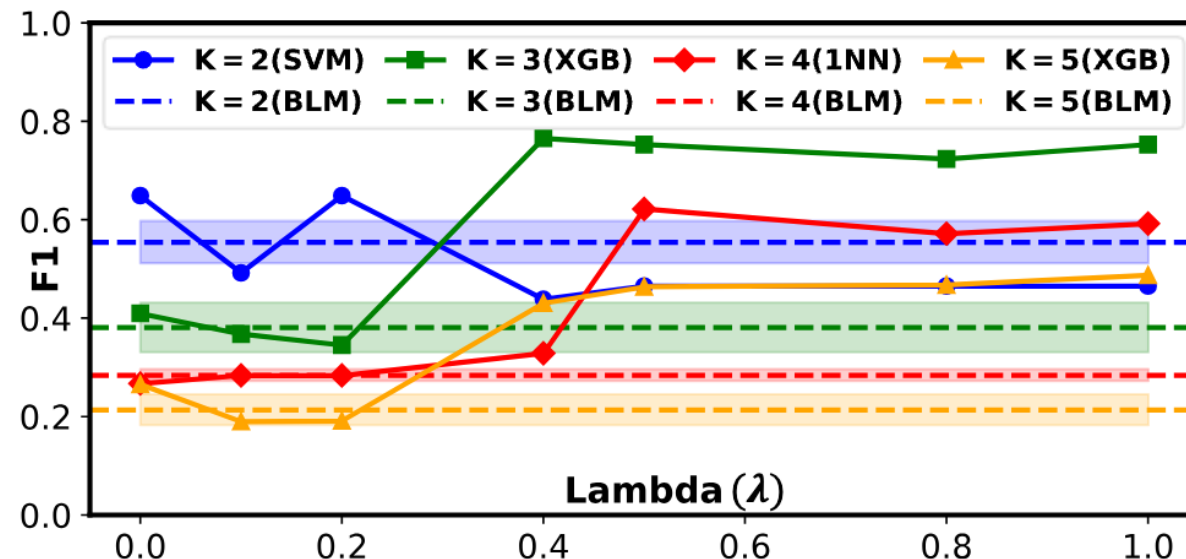


Figure 2: Best models with FuSE-MET vs. the average of models with baseline (no-fusion) for different clusters (K).

Key Findings

- FuSE-MET outperforms baselines in accuracy and F1 score.
- Optimal λ range (0.2-0.5) balances semantic and domain knowledge.
- Simpler models (e.g., 1NN, SVM) perform better due to reduced label complexity.
- K=3 achieves a higher F1 score (0.77) compared to K=2 (0.65).

K	Best λ	Best Classifier	ACC	PRE	REC	F1
2	0.2	SVM	0.98	0.69	0.62	0.65
	–	*GPT4+CNN	0.62	0.61	0.6	0.59
3	0.4	XGB	0.68	0.77	0.76	0.77
	–	*GPT4+XGB	0.63	0.57	0.51	0.51
4	0.5	1NN	0.69	0.63	0.62	0.62
	–	*GPT4+XGB	0.55	0.33	0.32	0.3
5	0.5	DANets	0.58	0.49	0.65	0.48
	–	*GPT4+1NN	0.47	0.32	0.29	0.3
36	No-Fusion	*1NN	0.27	0.18	0.19	0.18

Table 1: Best performances (on F1) of baselines and FuSE-MET with the classifiers. ‘*’ indicates baseline.

Conclusion

Summary:

- FuSE-MET bridges the gap in HAR for free-living environments by handling noisy labels and sparse data.
- Integrates semantic embeddings with MET values to reduce label complexity and improve classification.

Strengths:

- Outperforms state-of-the-art methods, including zero-shot GPT-4-based approaches.
- Simplifies HAR tasks, making them feasible for lightweight models in clinical and real-world settings.

Future Directions:

- Generalize to other uncontrolled domains and user populations.
- Investigate adaptive hyperparameter tuning for varying datasets.



AAAI-25



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Thank You!

Questions?

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