A Multi-Label Classification Framework for Cancer

Markian Jaworsky (u1101991)

Supervisors:
Principal supervisor Xiaohui Tao
Associate supervisors Jianming Yong, Ji Zhang, Lei Pan (External), Shiva Pokhrel (External)

School of Mathematics, Physics, and Computing, University of Southern Queensland, Australia

A presentation partially fulfil the requirements for the conformation of PhD candidature, August 11, 2022

Introduction

- A range of risk factors can be used as predictor variables in the likelihood of developing chronic illness. With awareness, patients can adapt their lifestyle in order to improve their chances of longer term survival.

Introduction

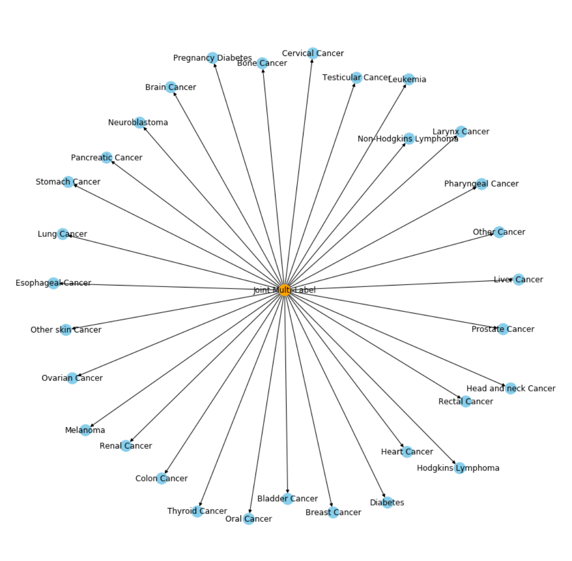
- Word cloud of text frequency variance between smoking and non-smoking lung cancer patients.

Introduction

- Most studies are typically focused on single disease datasets, however, to live a truly healthy lifestyle, the features that can be used to predict the likelihood of many diseases is more useful.

Research Scope - Goal

- A Framework for Handling the Data Challenges in the Multi-Label Classification of Multiple Cancer subtypes.



Research Scope - Problem

- Individual diseases have individual data patterns, in order to predict multiple diseases, we must be able to overcome the many data challenges that can occur.

Research Scope - Questions

- How can we introduce innovation and provide a framework for the identification of data patterns in the classification of cancer subtypes?
- Using agile methodology how do we development of a new framework for developing predictive models of multiple cancers, and multiple cancer occurrences?

Research Scope - Objectives

- Develop a robust approach to using health surveys for the construction of predictive models of multiple chronic illnesses.
- Identify the optimum subset of health survey predictor variables to classify the largest subset of multiple cancer subtypes.

Research Scope - Limitations and Assumptions

- This study is focused on the technical challenges of data, the topic of data privacy is outside the scope of the reviewed literature.

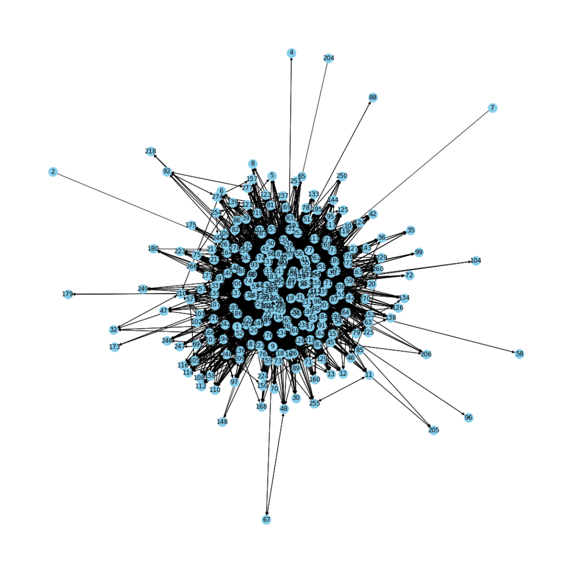
Research Scope - Expected Research Outcome 1

- A subset of predictor variables that can be robustly used to predict a level of risk in multiple cancer subtypes.

Research Scope - Expected Research Outcome 2

- A Framework for Handling the Data Challenges in the Multi-Label Classification of Multiple Chronic Illnesses.

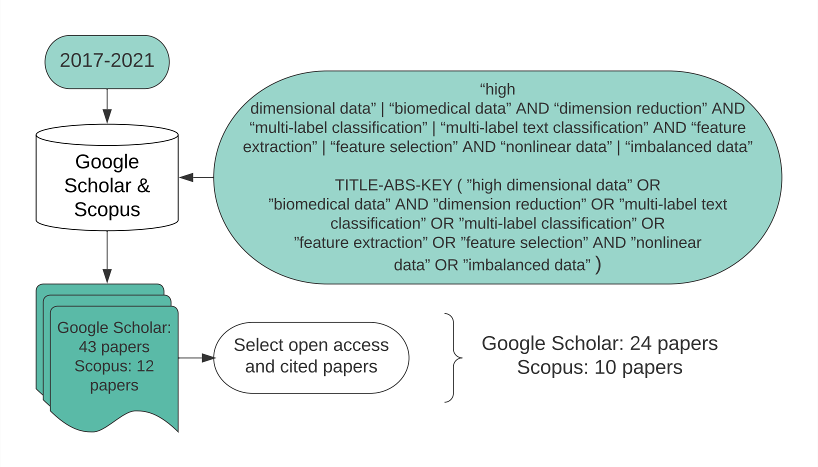
- Novel automated chapter ranking significance-based knowledge graph to identify inter-feature relations.



Research Scope - Potential Contribution 2

- Novel majority class under-sampling method that replaces nonlinear features with eliminated linear features.

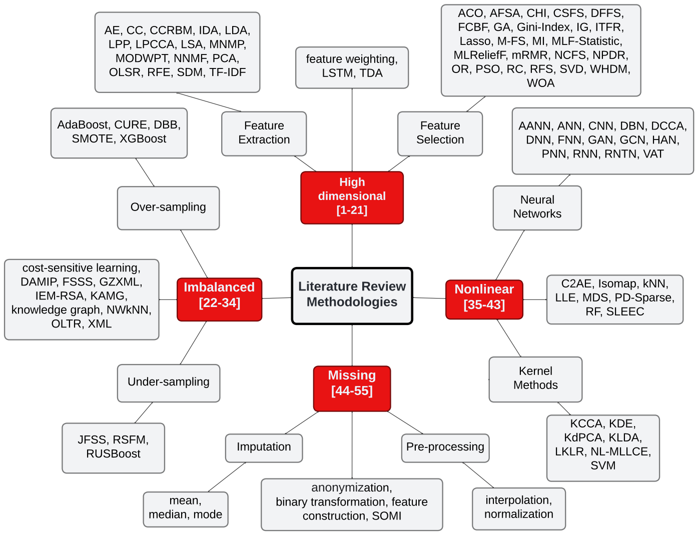
Literature Review - Scope



Literature Review - Data Challenges

- High Dimensional Datasets [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21]
- Imbalanced Class Datasets [22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34]
- Multiple and Nonlinear Datasets [35, 36, 37, 38, 39, 40, 41, 42, 43]
- Datasets with Missing and Erroneous Values [44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55]

Literature Review

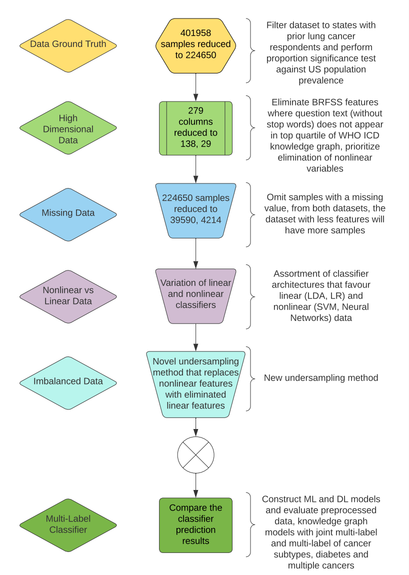


- There is not an existing single widely-adopted framework for uncovering data patterns to support the construction of multi-label chronic illness classifier.

Literature Review

- Therefore we are unable to satisfactorily state that RQ1 is adequately supported and proposed to conduct further research in order to answer RQ2.

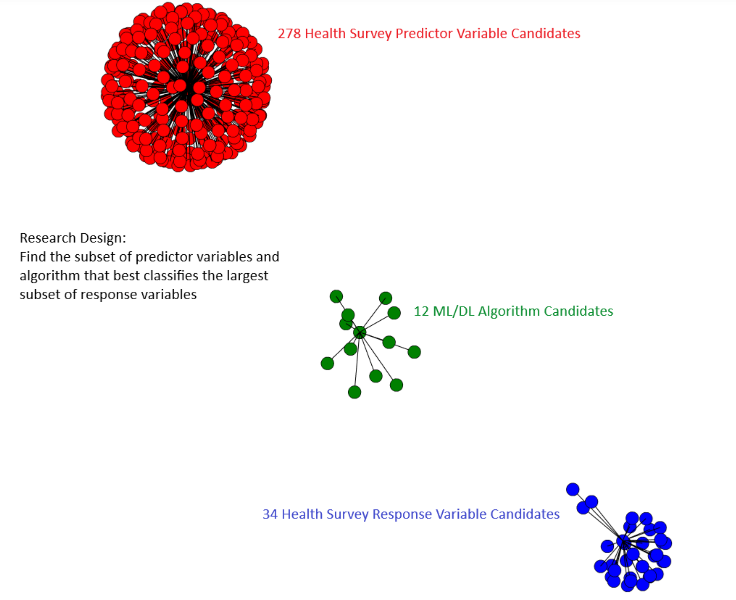
Research Design - Data Preparation



Research Design - Goal

- Reproducible health survey analysis and predictive model construction

Research Design



Research Design - Health Survey Classifiers

- AdaBoost [56]
- K-nearest neighbours [56, 57]
- Linear Discriminant Analysis [58]
- Logistic Regression [56, 57]
- Multinomial Naive Bayes [56]
- Random Forest [56, 57]
- RUSBoost [56]
- Support Vector Machine [56]
- TensorFlow Convolutional Neural Networks [56]

Research Design - Parameter Tuning Optimization

- Hyperopt [59, 60]
- Grid Search [61]
- ULMfit [62]

Research Design - Evaluation Methods

- Macro Average F1-Score [14, 18, 17, 11, 49, 22, 26, 29, 25, 43, 41, 51, 52, 8, 63, 64, 61, 65, 54, 66, 30, 67, 47, 68, 48, 69, 70, 71, 72, 7, 73, 74, 75, 76, 77]
- Precision at Top K (P@k) [17, 39, 40, 78, 79, 80, 81, 31, 63, 32, 34, 82, 83, 84, 60, 85, 73, 76, 86]

Research Design - Dataset

- The United States CDC and Prevention make available an anonymized annual Behavioral Risk Factor Surveillance System (BRFSS) survey data from across all 50 US states from the years 1985 to 2020, which is free to the public domain and may be copied and distributed without permission.
- The annual surveys consist of between 100 to 454 questions which vary from year to year and up to half a million respondents complete the surveys each year, and is the world's largest annual health survey.

Research Design - Baseline Dataset

- The baseline dataset to be used first applies a filter of the geographical state of the respondent, states eliminated from the dataset have been identified by searching through prior years of surveys and deselecting states with no lung cancer candidates.
- In order to establish a dataset that is representative of the ground truth, the BRFSS annual survey can be filtered by states until an insignificant proportion of lung cancer, a chronic illness with a high prevalence amongst both male and female patients, such that it is comparable to the prevalence of lung cancer in the population of the USA.

Research Plan - Phase 1

- Knowledge Graph-Based Feature Selection for Multi-Label Classification on Health Survey Data

Research Plan - Phase 2

- Automated Knowledge Graph Construction for Healthcare Domain

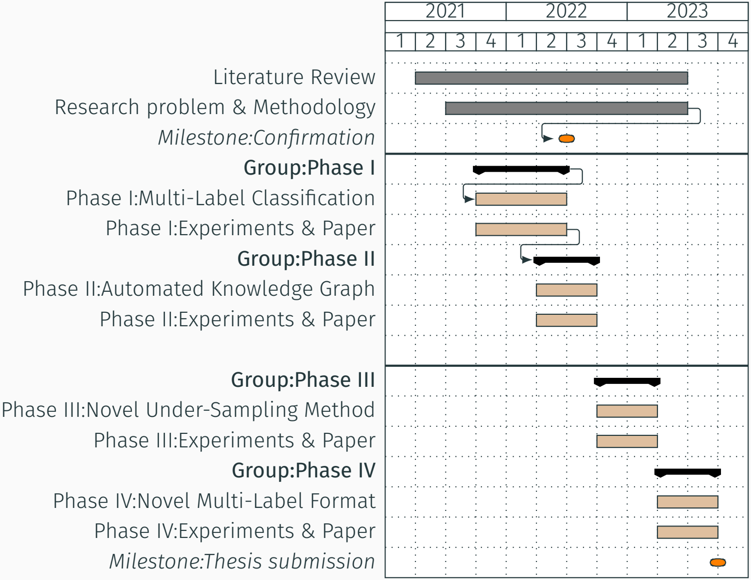
Research Plan - Phase 3

- Nonlinear with Linear Feature Replacement in Multi-Label Classification

Research Plan - Phase 4

- Construct a Multi-Label format which best classifies cancer subtypes

Timeline - Gantt Chart



Timeline - Dissemination plan

- Confirmation of Candidature Draft Submission: 02/08/2022
- Science Direct Artificial Intelligence in Medicine Submission: 30/04/2023

Progress To Date

- Biomedical Engineering Review IEEE Submission: 25/04/2022
- IEEE International Conference on Data Mining (ICDM 2022) Submission: 11/06/2022
- Springer International Conference on Health Information Systems Submission: 02/07/2022

Other Issues - Ethics Approval

- USQ HREC ID: H21REA222
- Approval date: 15/10/2021
- Expiry date: 15/10/2024
- USQ HREC status: Approved

Other Issues - Publication Acceptance

- Part-time study
- Publication acceptance time

Conclusion 1

- Feature engineering methods, such as deep neural networks, simultaneously extract and select features which leads to improved performance of the model classification.
- Imbalanced class datasets require training sets to have balanced class data, or appropriate metrics to assess the precision of minority class predictions.
- Features with missing values can be transformed into meaningful information, even in binary format, and both a subset of traditional ML and most deep learning techniques are adequate for the handling of nonlinear data.

Conclusion 2

- An ensemble of linear, nonlinear, and majority class undersampling multi-label classifiers can provide the best coverage for identifying and predicting true positive minority class samples.
- It was also observed that the usage of linear variables can be valuable when a dataset has imbalanced classes, and imputation methods for handling missing data should focus on the preservation of linear variables.

Conclusion 3

- We can automate the construction of a knowledge graph using a Wilcox rank significance test and in order to assist the selection of features that contain the highest and lowest levels of inter-feature relations.

References

[1] Marziyeh Arabnejad et al. "Nearest-Neighbor Projected Distance Regression for Epistasis Detection in GWAS With Population Structure Correction". In: *Frontiers in Genetics* 11 (2020). DOI: *10.3389/fgene.2020.00784*. URL: *https://doi.org/10.3389/fgene.2020.00784*.

[2] Alberto Cano, Sebastián Ventura, and Krzysztof J Cios. "Multi-objective genetic programming for feature extraction and data visualization". In: *Soft Computing* 21.8 (2017), pp. 2069–2089. DOI: *10.1007/s00500-015-1907-y*. URL: *https://doi.org/10.1007/s00500-015-1907-y*.

[3] Francisco Chinesta et al. "Virtual, digital and hybrid twins: a new paradigm in data-based engineering and engineered data". In: *Archives of computational methods in engineering* 27.1 (2020), pp. 105–134. DOI: 10.1007/s11831-018-9301-4. URL: https://doi.org/10.1007/s11831-018-9301-4.

[4] Travers Ching et al. "Opportunities and obstacles for deep learning in biology and medicine". In: *Journal of The Royal Society Interface* 15.141 (2018), p. 20170387. DOI: 10.1098/rsif.2017.0387. URL: https://doi.org/10.1098/rsif.2017.0387.

[5] Juying Dai et al. "Signal-based intelligent hydraulic fault diagnosis methods: Review and prospects". In: *Chinese Journal of Mechanical Engineering* 32.1 (2019), pp. 1–22. DOI: 10.1186/s10033-019-0388-9. URL: https://doi.org/10.1186/s10033-019-0388-9.

[6] Fei Deng et al. “Predict multicategory causes of death in lung cancer patients using clinicopathologic factors”. In: *Computers in Biology and Medicine* 129 (2021), p. 104161. DOI: *10.1016/j.compbiomed.2020.104161*. URL: *https://doi.org/10.1016/j.compbiomed.2020.104161*.

[7] Rania M Ghoniem, Nawal Alhelwa, and Khaled Shaalan. “A Novel Hybrid Genetic-Whale Optimization Model for Ontology Learning from Arabic Text”. In: *Algorithms* 12.9 (2019), p. 182. DOI: *10.3390/a12090182*. URL: *https://doi.org/10.3390/a12090182*.

[8] Hai Huang and Huan Liu. “Feature selection for hierarchical classification via joint semantic and structural information of labels”. In: *Knowledge-Based Systems* 195 (2020), p. 105655. DOI: *10.1016/j.knosys.2020.105655*. URL: *https://doi.org/10.1016/j.knosys.2020.105655*.

[9] Kwang-Ho In et al. "Lung cancer patients who are asymptomatic at diagnosis show favorable prognosis: a Korean Lung Cancer Registry Study". In: *Lung cancer* 64.2 (2009), pp. 232–237. DOI: 10.1016/j.lungcan.2008.08.005. URL: https://doi.org/10.1016/j.lungcan.2008.08.005.

[10] He Jiang. "Sparse estimation based on square root nonconvex optimization in high-dimensional data". In: *Neurocomputing* 282 (2018), pp. 122–135. DOI: 10.1016/j.neucom.2017.12.025. URL: https://doi.org/10.1016/j.neucom.2017.12.025.

[11] Kyoungok Kim. "An improved semi-supervised dimensionality reduction using feature weighting: application to sentiment analysis". In: *Expert Systems with Applications* 109 (2018), pp. 49–65. DOI: 10.1016/j.eswa.2018.05.023. URL: https://doi.org/10.1016/j.eswa.2018.05.023.

References v

[12] Li Ma and Suohai Fan. “CURE-SMOTE algorithm and hybrid algorithm for feature selection and parameter optimization based on random forests”. In: *BMC bioinformatics* 18.1 (2017), pp. 1–18. DOI: *10.1186/s12859-017-1578-z*. URL: *https://doi.org/10.1186/s12859-017-1578-z*.

[13] Mahla Mokhtia, Mahdi Eftekhari, and Farid Saberi-Movahed. “Feature selection based on regularization of sparsity based regression models by hesitant fuzzy correlation”. In: *Applied Soft Computing* 91 (2020), p. 106255. DOI: *10.1016/j.asoc.2020.106255*. URL: *https://doi.org/10.1016/j.asoc.2020.106255*.

[14] Kwang Ho Park et al. “Deep Learning Feature Extraction Approach for Hematopoietic Cancer Subtype Classification”. In: *International Journal of Environmental Research and Public Health* 18.4 (2021), p. 2197. DOI: *10.3390/ijerph18042197*. URL: *https://doi.org/10.3390/ijerph18042197*.

[15] Julliano Trindade Pintas, Leandro AF Fernandes, and Ana Cristina Bicharra Garcia. "Feature selection methods for text classification: a systematic literature review". In: *Artificial Intelligence Review* (2021), pp. 1–52. DOI: *10.1007/s10462-021-09970-6*. URL: *https://doi.org/10.1007/s10462-021-09970-6*.

[16] Wenbin Qian et al. "Mutual information-based label distribution feature selection for multi-label learning". In: *Knowledge-Based Systems* 195 (2020), p. 105684. DOI: *10.1016/j.knosys.2020.105684*. URL: *https://doi.org/10.1016/j.knosys.2020.105684*.

[17] Wissam Siblini, Pascale Kuntz, and Frank Meyer. "A review on dimensionality reduction for multi-label classification". In: *IEEE Transactions on Knowledge and Data Engineering* 33.3 (2019), pp. 839–857. DOI: *10.1109/TKDE.2019.2940014*. URL: *https://doi.org/10.1109/TKDE.2019.2940014*.

[18] Abdellah Tebani, Carlos Afonso, and Soumeya Bekri. "Advances in metabolome information retrieval: turning chemistry into biology. Part II: biological information recovery". In: *Journal of inherited metabolic disease* 41.3 (2018), pp. 393–406. DOI: *10.1007/s10545-017-0080-0*. URL: *https://doi.org/10.1007/s10545-017-0080-0*.

[19] Lokeswari Venkataramana, Shomona Gracia Jacob, and Rajavel Ramadoss. "A parallel multilevel feature selection algorithm for improved cancer classification". In: *Journal of Parallel and Distributed Computing* 138 (2020), pp. 78–98. DOI: *10.1016/j.jpdc.2019.12.015*. URL: *https://doi.org/10.1016/j.jpdc.2019.12.015*.

[20] Xinzheng Xu et al. “Review of classical dimensionality reduction and sample selection methods for large-scale data processing”. In: *Neurocomputing* 328 (2019), pp. 5–15. DOI: 10.1016/j.neucom.2018.02.100. URL: https://doi.org/10.1016/j.neucom.2018.02.100.

[21] Mingwei Zhang, Ziqi Ji, and Zebo Dong. “Classification based on label semantic characteristic analysis”. In: *2017 2nd Asia-Pacific Conference on Intelligent Robot Systems (ACIRS)*. IEEE. 2017, pp. 78–82. DOI: 10.1109/ACIRS.2017.7986069. URL: https://doi.org/10.1109/ACIRS.2017.7986069.

[22] Meng Liu et al. “Cost-sensitive feature selection via f-measure optimization reduction”. In: *Thirty-First AAAI Conference on Artificial Intelligence*. 2017. URL: https://ojs.aaai.org/index.php/AAAI/article/view/10770.

[23] FY Chin, CA Lim, and KH Lem. "Handling leukaemia imbalanced data using synthetic minority oversampling technique (SMOTE)". In: *Journal of Physics: Conference Series*. Vol. 1988. IOP Publishing. 2021, p. 012042. DOI: 10.1088/1742-6596/1988/1/012042. URL: https://doi.org/10.1088/1742-6596/1988/1/012042.

[24] Risky Frasetio Wahyu Pratama, Santi Wulan Purnami, and Santi Puteri Rahayu. "Boosting support vector machines for imbalanced microarray data". In: *Procedia computer science* 144 (2018), pp. 174–183. DOI: 10.1016/j.procs.2018.10.517. URL: https://doi.org/10.1016/j.procs.2018.10.517.

[25] Xuchun Wang et al. "Exploratory study on classification of diabetes mellitus through a combined Random Forest Classifier". In: *BMC medical informatics and decision making* 21.1 (2021), pp. 1–14. DOI: 10.1186/s12911-021-01471-4. URL: https://doi.org/10.1186/s12911-021-01471-4.

[26] Barbara Pes. "Learning from High-Dimensional and Class-Imbalanced Datasets Using Random Forests". In: *Information* 12.8 (2021), p. 286. DOI: *10.3390/info12080286*. URL: *https://doi.org/10.3390/info12080286*.

[27] Aliaksandr Barushka and Petr Hajek. "Spam filtering using integrated distribution-based balancing approach and regularized deep neural networks". In: *Applied Intelligence* 48.10 (2018), pp. 3538–3556. DOI: *10.1007/s10489-018-1161-y*. URL: *https://doi.org/10.1007/s10489-018-1161-y*.

[28] Xuedong Li et al. "Improving rare disease classification using imperfect knowledge graph". In: *BMC medical informatics and decision making* 19.5 (2019), pp. 1–10. DOI: *10.1186/s12911-019-0938-1*. URL: *https://doi.org/10.1186/s12911-019-0938-1*.

[29] Patrícia Gonzalez-Dias et al. "Methods for predicting vaccine immunogenicity and reactogenicity". In: *Human vaccines & immunotherapeutics* 16.2 (2020), pp. 269–276. DOI: 10.1080/21645515.2019.1697110. URL: https://doi.org/10.1080/21645515.2019.1697110.

[30] Linchao Zhu and Yi Yang. "Inflated episodic memory with region self-attention for long-tailed visual recognition". In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2020, pp. 4344–4353. DOI: 10.1109/CVPR42600.2020.00440. URL: https://doi.org/10.1109/CVPR42600.2020.00440.

[31] Jingjing Li et al. "On both cold-start and long-tail recommendation with social data". In: *IEEE Transactions on Knowledge and Data Engineering* 33.1 (2019), pp. 194–208. DOI: 10.1109/TKDE.2019.2924656. URL: https://doi.org/10.1109/TKDE.2019.2924656.

[32] Tharun Medini, Beidi Chen, and Anshumali Shrivastava. "SOLAR: Sparse Orthogonal Learned and Random Embeddings". In: *arXiv preprint arXiv:2008.13225* (2020). URL: *https://arxiv.org/abs/2008.13225*.

[33] Wei-Cheng Chang et al. "Pre-training tasks for embedding-based large-scale retrieval". In: *arXiv preprint arXiv:2002.03932* (2020). URL: *https://arxiv.org/abs/2002.03932*.

[34] Shanshan Wu et al. "Learning a compressed sensing measurement matrix via gradient unrolling". In: *International Conference on Machine Learning*. PMLR. 2019, pp. 6828–6839. URL: *https://arxiv.org/abs/1806.10175*.

[35] Mingda Li, Weiting Gao, and Yi Chen. "A Topic and Concept Integrated Model for Thread Recommendation in Online Health Communities". In: *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*. 2020, pp. 765–774. DOI: 10.1145/3340531.3411933. URL: https://doi.org/10.1145/3340531.3411933.

[36] Betty van Aken et al. "Clinical outcome prediction from admission notes using self-supervised knowledge integration". In: *arXiv preprint arXiv:2102.04110* (2021). URL: https://arxiv.org/abs/2102.04110.

[37] Stephen L France and Sanjoy Ghose. "Marketing analytics: Methods, practice, implementation, and links to other fields". In: *Expert Systems with Applications* 119 (2019), pp. 456–475. DOI: 10.1016/j.eswa.2018.11.002. URL: https://doi.org/10.1016/j.eswa.2018.11.002.

[38] Xinghao Yang et al. "A survey on canonical correlation analysis". In: *IEEE Transactions on Knowledge and Data Engineering* (2019). DOI: 10.1109/TKDE.2019.2958342. URL: https://doi.org/10.1109/TKDE.2019.2958342.

[39] Wenjie Zhang et al. "Deep extreme multi-label learning". In: *Proceedings of the 2018 ACM on International Conference on Multimedia Retrieval*. 2018, pp. 100–107. URL: https://arxiv.org/abs/1704.03718.

[40] Weiwei Liu and Xiaobo Shen. "Sparse extreme multi-label learning with oracle property". In: *International Conference on Machine Learning*. PMLR. 2019, pp. 4032–4041. URL: https://proceedings.mlr.press/v97/liu19d.html.

[41] Chao Tan and Genlin Ji. “LKLR: A local tangent space-alignment kernel least-squares regression algorithm”. In: *Tsinghua Science and Technology* 24.4 (2019), pp. 389–399. DOI: *10.26599/TST.2018.9010120*. URL: *https://doi.org/10.26599/TST.2018.9010120*.

[42] Jia Chen, Gang Wang, and Georgios B Giannakis. “Nonlinear dimensionality reduction for discriminative analytics of multiple datasets”. In: *IEEE Transactions on Signal Processing* 67.3 (2018), pp. 740–752. DOI: *10.1109/TSP.2018.2885478*. URL: *https://doi.org/10.1109/TSP.2018.2885478*.

[43] Shu-Kai S Fan et al. “Defective wafer detection using a denoising autoencoder for semiconductor manufacturing processes”. In: *Advanced Engineering Informatics* 46 (2020), p. 101166. DOI: *10.1016/j.aei.2020.101166*. URL: *https://doi.org/10.1016/j.aei.2020.101166*.

[44] Omogbai Oleghe. "A predictive noise correction methodology for manufacturing process datasets". In: *Journal of Big Data* 7.1 (2020), pp. 1–27. DOI: 10.1186/s40537-020-00367-w. URL: https://doi.org/10.1186/s40537-020-00367-w.

[45] Michael P Bancks et al. "Epidemiology of diabetes phenotypes and prevalent cardiovascular risk factors and diabetes complications in the National Health and Nutrition Examination Survey 2003–2014". In: *Diabetes research and clinical practice* 158 (2019), p. 107915. DOI: 10.1016/j.diabres.2019.107915. URL: https://doi.org/10.1016/j.diabres.2019.107915.

[46] Emmanouil Antonios Platanios et al. "Learning from Imperfect Annotations: An End-to-End Approach". In: (2019). URL: https://openreview.net/forum?id=rJlVdREKDS.

[47] Stefano Melacci et al. "Domain Knowledge Alleviates Adversarial Attacks in Multi-Label Classifiers". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2021). DOI: *10.1109/TPAMI.2021.3137564*. URL: *https://doi.org/10.1109/TPAMI.2021.3137564*.

[48] Nanyang Wang et al. "Pixel2mesh: 3d mesh model generation via image guided deformation". In: *IEEE transactions on pattern analysis and machine intelligence* (2020). DOI: *10.1109/TPAMI.2020.2984232*. URL: *https://doi.org/10.1109/TPAMI.2020.2984232*.

[49] Youqiang Zhang et al. "A novel ensemble method for k-nearest neighbor". In: *Pattern Recognition* 85 (2019), pp. 13–25. DOI: *10.1016/j.patcog.2018.08.003*. URL: *https://doi.org/10.1016/j.patcog.2018.08.003*.

[50] Bertrand De Meulder et al. "A computational framework for complex disease stratification from multiple large-scale datasets". In: *BMC systems biology* 12.1 (2018), pp. 1–23. DOI: 10.1186/s12918-018-0556-z. URL: https://doi.org/10.1186/s12918-018-0556-z.

[51] Bain Khusnul Khotimah, Miswanto Miswanto, and Herry Suprajitno. "Optimization of feature selection using genetic algorithm in naïve Bayes classification for incomplete data". In: *Int. J. Intell. Eng. Syst* 13.1 (2020), pp. 334–343. DOI: 10.22266/ijies2020.0229.31. URL: https://doi.org/10.22266/ijies2020.0229.31.

[52] Muhammad Adil et al. "LSTM and bat-based RUSBoost approach for electricity theft detection". In: *Applied Sciences* 10.12 (2020), p. 4378. DOI: 10.3390/app10124378. URL: https://doi.org/10.3390/app10124378.

[53] Sakib Mahmud Khan et al. "Multi-class twitter data categorization and geocoding with a novel computing framework". In: *Cities* 96 (2020), p. 102410. DOI: 10.1016/j.cities.2019.102410. URL: https://doi.org/10.1016/j.cities.2019.102410.

[54] Khan Md Hasib et al. "A Novel Deep Learning based Sentiment Analysis of Twitter Data for US Airline Service". In: *2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD)*. IEEE. 2021, pp. 450–455. DOI: 10.1109/ICICT4SD50815.2021.9396879. URL: https://doi.org/10.1109/ICICT4SD50815.2021.9396879.

[55] Doyen Sahoo, Chenghao Liu, and Steven CH Hoi. "Malicious URL detection using machine learning: A survey". In: *arXiv preprint arXiv:1701.07179* (2017). URL: https://arxiv.org/abs/1701.07179.

[56] R Prashanth and Sumantra Dutta Roy. "Novel and improved stage estimation in Parkinson's disease using clinical scales and machine learning". In: *Neurocomputing* 305 (2018), pp. 78–103.

[57] Fikrewold H Bitew et al. "Machine learning approach for predicting under-five mortality determinants in Ethiopia: evidence from the 2016 Ethiopian Demographic and Health Survey". In: *Genus* 76.1 (2020), pp. 1–16.

[58] Carlo Ricciardi et al. "Linear discriminant analysis and principal component analysis to predict coronary artery disease". In: *Health informatics journal* 26.3 (2020), pp. 2181–2192.

[59] Ilias Chalkidis et al. "Large-scale multi-label text classification on EU legislation". In: *arXiv preprint arXiv:1906.02192* (2019). DOI: 10.18653/v1/P19-1636. URL: https://doi.org/10.18653/v1/P19-1636.

[60] Ilias Chalkidis et al. “Extreme multi-label legal text classification: A case study in EU legislation”. In: *arXiv preprint arXiv:1905.10892* (2019). DOI: *10.18653/v1/W19-2209*. URL: *https://doi.org/10.18653/v1/W19-2209*.

[61] Louis Létinier et al. “Artificial intelligence for unstructured healthcare data: application to coding of patient reporting of adverse drug reactions”. In: *Clinical Pharmacology & Therapeutics* (2021). DOI: *10.1002/cpt.2266*. URL: *https://doi.org/10.1002/cpt.2266*.

[62] Zein Shaheen, Gerhard Wohlgenannt, and Erwin Filtz. “Large scale legal text classification using transformer models”. In: *arXiv preprint arXiv:2010.12871* (2020). URL: *https://arxiv.org/abs/2010.12871*.

[63] Dezhao Song et al. "Multi-label legal document classification: A deep learning-based approach with label-attention and domain-specific pre-training". In: *Information Systems* (2021), p. 101718. DOI: 10.1016/j.is.2021.101718. URL: https://doi.org/10.1016/j.is.2021.101718.

[64] Kathryn Annette Chapman and Günter Neumann. "Automatic ICD Code Classification with Label Description Attention Mechanism.". In: *IberLEF@ SEPLN*. 2020, pp. 477–488. URL: https://www.semanticscholar.org/paper/Automatic-ICD-Code-Classification-with-Label-Chapman-Neumann/af3247725d9327857d922f17078b73cd1cba3f49.

[65] Pengkai Zhu, Hanxiao Wang, and Venkatesh Saligrama. “Generalized zero-shot recognition based on visually semantic embedding”. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2019, pp. 2995–3003. URL: https://arxiv.org/abs/1811.07993.

[66] Jian Wang et al. “Deep metric learning with angular loss”. In: *Proceedings of the IEEE International Conference on Computer Vision*. 2017, pp. 2593–2601. URL: https://arxiv.org/abs/1708.01682.

[67] Muhammad Ali Ibrahim et al. “GHS-NET a generic hybridized shallow neural network for multi-label biomedical text classification”. In: *Journal of Biomedical Informatics* 116 (2021), p. 103699. DOI: 10.1016/j.jbi.2021.103699. URL: https://doi.org/10.1016/j.jbi.2021.103699.

[68] Pengkai Zhu, Hanxiao Wang, and Venkatesh Saligrama. "Learning classifiers for target domain with limited or no labels". In: *International Conference on Machine Learning*. PMLR. 2019, pp. 7643–7653. URL: https://proceedings.mlr.press/v97/zhu19d.html.

[69] Lihi Dery. "Multi-label Ranking: Mining Multi-label and Label Ranking Data". In: *arXiv preprint arXiv:2101.00583* (2021). URL: https://arxiv.org/abs/2101.00583.

[70] Pedro Ruas et al. “LasigeBioTM at CANTEMIST: Named Entity Recognition and Normalization of Tumour Morphology Entities and Clinical Coding of Spanish Health-related Documents.”. In: *IberLEF@ SEPLN*. 2020, pp. 422–437. URL: https://www.researchgate.net/publication/344429519_LasigeBioTM_at_CANTEMIST_Named_Entity_Recognition_and_Normalization_of_Tumour_Morphology_Entities_and_Clinical_Coding_of_Spanish_Health-related_Documents.

[71] Jiayu Wu. “Leveraging Label Information in Representation Learning for Multi-label Text Classication”. PhD thesis. UCLA, 2019. URL: https://escholarship.org/uc/item/3870d965.

[72] Donna Xu et al. "Survey on multi-output learning". In: *IEEE transactions on neural networks and learning systems* 31.7 (2019), pp. 2409–2429. DOI: 10.1109/TNNLS.2019.2945133. URL: https://doi.org/10.1109/TNNLS.2019.2945133.

[73] Qian Li et al. "A survey on text classification: From shallow to deep learning". In: *arXiv preprint arXiv:2008.00364* (2020). URL: https://arxiv.org/abs/2008.00364.

[74] Willem Waegeman, Krzysztof Dembczyński, and Eyke Hüllermeier. "Multi-target prediction: a unifying view on problems and methods". In: *Data Mining and Knowledge Discovery* 33.2 (2019), pp. 293–324. DOI: 10.1007/s10618-018-0595-5. URL: https://doi.org/10.1007/s10618-018-0595-5.

[75] Rafael Leal. “Unsupervised zero-shot classification of Finnish documents using pre-trained language models”. PhD thesis. University of Helsinki, 2020. URL: http://urn.fi/URN:NBN:fi:hulib-202012155147.

[76] Kalina Jasinska-Kobus et al. “Probabilistic label trees for extreme multi-label classification”. In: *arXiv preprint arXiv:2009.11218* (2020). URL: https://arxiv.org/abs/2009.11218.

[77] Jinseok Nam. “Learning Label Structures with Neural Networks for Multi-label Classification”. PhD thesis. Technische Universität, 2019. URL: https://tuprints.ulb.tu-darmstadt.de/id/eprint/8738.

[78] Elham J Barezi, James T Kwok, and Hamid R Rabiee. “Multi-Label learning in the independent label sub-spaces”. In: *Pattern Recognition Letters* 97 (2017), pp. 8–12. DOI: 10.1016/j.patrec.2017.06.024. URL: https://doi.org/10.1016/j.patrec.2017.06.024.

[79] Bingyu Wang et al. “Ranking-based autoencoder for extreme multi-label classification”. In: *arXiv preprint arXiv:1904.05937* (2019). URL: *https://arxiv.org/abs/1904.05937*.

[80] Abhilash Gaure et al. “A probabilistic framework for zero-shot multi-label learning”. In: *The Conference on Uncertainty in Artificial Intelligence (UAI)*. Vol. 1. 2017, p. 3. URL: *https://www.semanticscholar.org/paper/A-Probabilistic-Framework-for-Multi-Label-Learning-Gaure-Rai/9c259f81257355f1e6a386d5f9ea5e4fe7744447*.

[81] Nilesh Gupta et al. “Generalized Zero-Shot Extreme Multi-label Learning”. In: *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*. 2021, pp. 527–535. DOI: *10.1145/3447548.3467426*. URL: *https://doi.org/10.1145/3447548.3467426*.

[82] Sihong Xie and Philip S Yu. “Active zero-shot learning: a novel approach to extreme multi-labeled classification”. In: *International Journal of Data Science and Analytics* 3.3 (2017), pp. 151–160. DOI: *10.1007/s41060-017-0042-5*. URL: *https://doi.org/10.1007/s41060-017-0042-5*.

[83] Anthony Rios and Ramakanth Kavuluru. “EMR coding with semi–parametric multi–head matching networks”. In: *Proceedings of the conference. Association for Computational Linguistics. North American Chapter. Meeting*. Vol. 2018. NIH Public Access. 2018, p. 2081. DOI: *10.18653/v1/N18-1189*. URL: *https://doi.org/10.18653/v1/N18-1189*.

[84] Kalina Jasinska-Kobus et al. “Online probabilistic label trees”. In: *International Conference on Artificial Intelligence and Statistics*. PMLR. 2021, pp. 1801–1809. URL: *https://arxiv.org/abs/2007.04451*.

[85] Purvi Prajapati and Amit Thakkar. "Performance improvement of extreme multi-label classification using K-way tree construction with parallel clustering algorithm". In: *Journal of King Saud University-Computer and Information Sciences* (2021). DOI: 10.1016/j.jksuci.2021.02.014. URL: https://doi.org/10.1016/j.jksuci.2021.02.014.

[86] Steven CH Hoi et al. "Online learning: A comprehensive survey". In: *Neurocomputing* 459 (2021), pp. 249–289. DOI: 10.1016/j.neucom.2021.04.112. URL: https://doi.org/10.1016/j.neucom.2021.04.112.

Thanks

Questions?

Markian Jaworsky
Markian.Jaworsky@usq.edu.au