Cohesive D&D Encounter Generator

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Content

- Dungeons and Dragons.
- Research Problem.
- Literature Survey.
- Progress map.

Dungeons and Dragons

Dungeons and Dragons

- Open ended, table-top roleplay game.
- Since 1974 , now in 5th edition [1].
- Predefined rules for gameplay [2-4].
- Several settings.
- Lore for each setting.
- History, status, relationships, description.

[1] J. Crawford, J. Wyatt, R. J. Schwalb, and B. R. Cordell, Player's Handbook. Wizards of the Coast LLC, 2014.
[2] Peiris, A., & de Silva, N. (2022, October). Synthesis and Evaluation of a Domain-specific Large Data Set for Dungeons & Dragons. In *Proceedings of the 36th Pacific Asia Conference on Language, Information and Computation* (pp. 415-424).
[3] K. Squire, Open-ended video games: A model for developing learning for the interactive age. MacArthur Foundation Digital Media and Learning Initiative, 2007.
[4] A. Peiris and N. de Silva, "SHADE: Semantic Hypernym Annotator for Domain-Specific Entities-Dungeons and Dragons Domain Use Case," in 2023 IEEE 17th International Conference on Industrial and Information Systems (ICIIS). IEEE, 2023, pp. 1–6.

Combat encounters

- Players vs “monsters”.
- The way to attain progress [5].
- Immersion and verisimilitude [6].
- Need to align with lore.

[5] J. Crawford, C. Perkins, and J. Wyatt, Dungeon Master’s Guide. Wizards of the Coast LLC, 2014.
[6] E. Stern, “A touch of medieval: Narrative, magic and computer technology in massively multiplayer computer role-playing games.” in CGDC Conf., 2002.

Research Problem

Research Problem

"Given a text prompt and/or relevant numerical values, creating cohesive D&D encounters with monsters and situations that align with the lore."

- No encounter generator to select monsters automatically according to lore.
- No encounter generator to select monsters automatically according to desired difficulty.
- Dungeon masters need to try various combinations.
- Automatic generation remains a gap.

Literature Survey

Encounter Generation

- Publicly available online tools[1][2][3].
    - Most of these tools use challenge rating system
    - Calculates XP point thresholds for player level inputs.
    - When a player selects monsters, calculates XP points for the monster combination.
    - Based on threshold, outputs the difficulty.

1 https://www.dndbeyond.com/encounter-builder
2 https://www.aidedd.org/dnd-encounter/
3 https://www.kassoon.com/dnd/5e/generate-encounter/

Existing works on DnD

- Forgotten Realms Wiki (FRW) dataset [8].
    - 11 datasets.
        - FRW-P (plain text) and FRW-J (Json) datasets.
        - FRW-I (Wiki infobox) dataset.
        - Word2Vec, Doc2Vec and PoinCare embeddings.
    - Free text generator.
    - Named entity classifier.

[8] Peiris, A., & de Silva, N. (2022, October). Synthesis and Evaluation of a Domain-specific Large Data Set for Dungeons & Dragons. In *Proceedings of the 36th Pacific Asia Conference on Language, Information and Computation* (pp. 415-424).

Named Entity Recognition Models

- LSTM, CNN and CRF based models.
  - Bi-LSTM-CRF [9] , Bi-LSTM-Bi-CRF [10].
  - Bi-LSTM-CNN [11].
- Contextualized string representations [12].
- Pre trained transformer based models.
  - BERT [13] with sequence tagging layer.
  - FLERT [14], Luoma and Pyysalo [15].

[9] G. Lample, M. Ballesteros, S. Subramanian, K. Kawakami, and C. Dyer, “Neural architectures for named entity recognition,” arXiv preprint arXiv:1603.01360, 2016.
[10] R. Panchendrarajan and A. Amaresan, “Bidirectional lstm-crf for named entity recognition,” in Proceedings of the 32nd Pacific Asia conference on language, information and computation, 2018.
[11] J. P. Chiu and E. Nichols, “Named entity recognition with bidirectional lstm-cnns,” Transactions of the association for computational linguistics, vol. 4, pp.357–370, 2016.
[12] A. Akbik, D. Blythe, and R. Vollgraf, “Contextual string embeddings for sequence labeling,” in Proceedings of the 27th international conference on computational linguistics, 2018, pp. 1638–1649.
[13] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “Bert: Pre-training of deep bidirectional transformers for language understanding,” arXiv preprint arXiv:1810.04805, 2018.
[14] S. Schweter and A. Akbik, “Flert: Document-level features for named entity recognition,” arXiv preprint arXiv:2011.06993, 2020.
[15] J. Luoma and S. Pyysalo, “Exploring cross-sentence contexts for named entity recognition with bert,” in Proceedings of the 28th International Conference on Computational Linguistics, 2020, pp. 904–914.

Named Entity Recognition Frameworks

- Trankit [16].
- Stanza [17].
- FLAIR [18].
    - Contextualised string representation model.
    - FLERT.
- spaCy[4].

[16] M. Van Nguyen, V. D. Lai, A. P. B. Veyseh, and T. H. Nguyen, “Trankit: A light-weight transformerbased toolkit for multilingual natural language processing,” arXiv preprint arXiv:2101.03289, 2021.
[17] P. Qi, Y. Zhang, Y. Zhang, J. Bolton, and C. D. Manning, “Stanza: A python natural language processing toolkit for many human languages,” arXiv preprint arXiv:2003.07082, 2020.
[18] A. Akbik, T. Bergmann, D. Blythe, K. Rasul, S. Schweter, and R. Vollgraf, “Flair: An easy-to-use framework for state-of-the-art nlp,” in Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics (demonstrations), 2019, pp. 54–59.

4 https://spacy.io/

Coreference resolution

- End to end deep learning models.
  - Optimizing the margin likelihood of antecedent spans [16].
  - Iterative span ranking architecture [17].
- Language representation models.
  - BERT for span ranking [18].

[16] K. Lee, L. He, M. Lewis, and L. Zettlemoyer, “End-to-end neural coreference resolution,” arXiv preprint arXiv:1707.07045, 2017.
[17] K. Lee, L. He, and L. Zettlemoyer, “Higher-order coreference resolution with coarse-to-fine inference,” in Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Short Papers), M. Walker, H. Ji, and A. Stent, Eds. New Orleans, Louisiana: Association for Computational Linguistics, Jun. 2018, pp. 687–692. [Online]. Available: https://aclanthology.org/N18-2108
[18] M. Joshi, O. Levy, D. S. Weld, and L. Zettlemoyer, “Bert for coreference resolution: Baselines and analysis,” arXiv preprint arXiv:1908.09091, 2019.

Word Embeddings

- Vector representations for words.
  - One hot encoding.
  - Bag of words.
- Word2Vec [19].
  - CBOW.
  - Skip gram embeddings.
- GloVe [20].
- FastText [21].

[19] T. Mikolov, K. Chen, G. Corrado, and J. Dean, “Efficient estimation of word representations in vector space,” arXiv preprint arXiv:1301.3781, 2013.
[20] Pennington, J., Socher, R., & Manning, C. D. (2014, October). Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP) (pp. 1532-1543).
[21] Bojanowski, P., Grave, E., Joulin, A., & Mikolov, T. (2017). Enriching word vectors with subword information. Transactions of the association for computational linguistics, 5, 135-146.

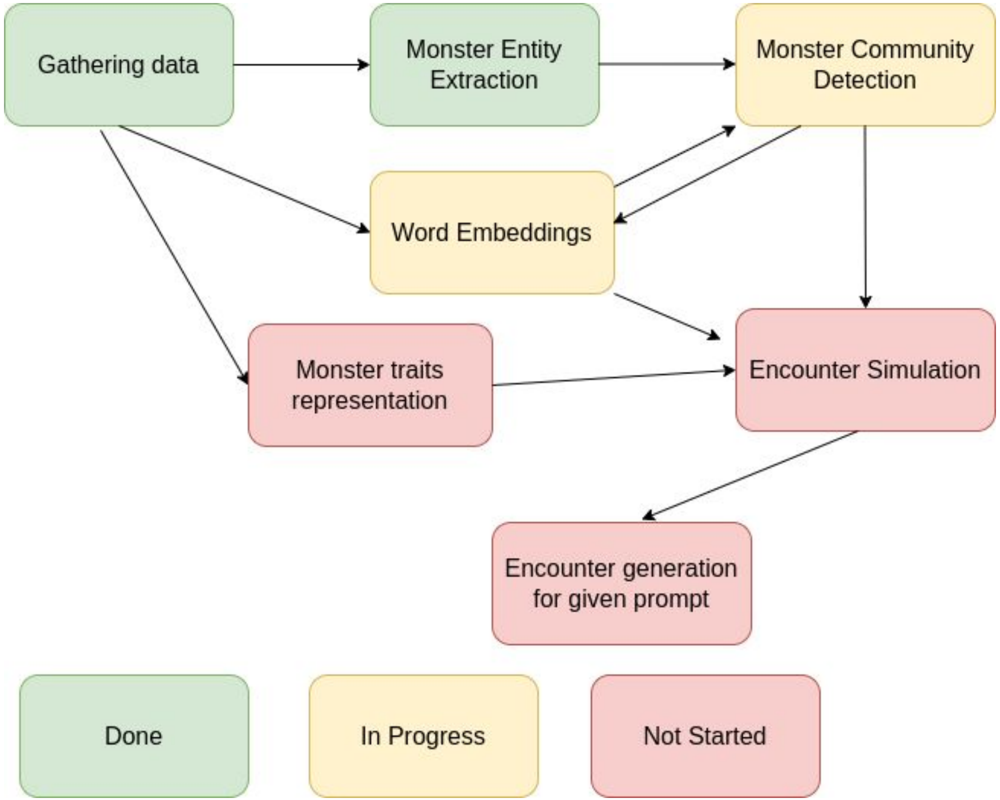
Community Detection

- Traditional methods.
  - Modularity based methods [22,23].
  - Label propagation based methods [24].
- Deep learning based methods.
  - Communitygan [25].
  - Non-negative Matrix Factorization [26,27].
  - Graph neural networks [28,29].

[22] V. D. Blondel, J.-L. Guillaume, R. Lambiotte, and E. Lefebvre, “Fast unfolding of communities in large networks,” Journal of statistical mechanics: theory and experiment, vol. 2008, no. 10, p. P10008, 2008.
[23] V. A. Traag, “Faster unfolding of communities: Speeding up the louvain algorithm,” Physical Review E, vol. 92, no. 3, p. 032801, 2015.
[24] U. N. Raghavan, R. Albert, and S. Kumara, “Near linear time algorithm to detect community structures in large-scale networks,” Physical review E, vol. 76, no. 3, p. 036106, 2007.
[25] Y. Jia, Q. Zhang, W. Zhang, and X. Wang, “Communitygan: Community detection with generative adversarial nets,” in The World Wide Web Conference, 2019, pp. 784–794.
[26] Y. Li, C. Sha, X. Huang, and Y. Zhang, “Community detection in attributed graphs: An embedding approach,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 32, no. 1, 2018.
[27] F. Ye, C. Chen, and Z. Zheng, “Deep autoencoder-like nonnegative matrix factorization for community detection,” in Proceedings of the 27th ACM international conference on information and knowledge management, 2018, pp. 1393–1402.
[28] Z. Chen, X. Li, and J. Bruna, “Supervised community detection with line graph neural networks,” arXiv preprint arXiv:1705.08415, 2017.
[29] D. Jin, Z. Liu, W. Li, D. He, and W. Zhang, “Graph convolutional networks meet markov random fields: Semi-supervised community detection in attribute networks,” in Proceedings of the AAAI conference on artificial intelligence, vol. 33, no. 01, 2019, pp. 152–159.

Progress Map

Progress map



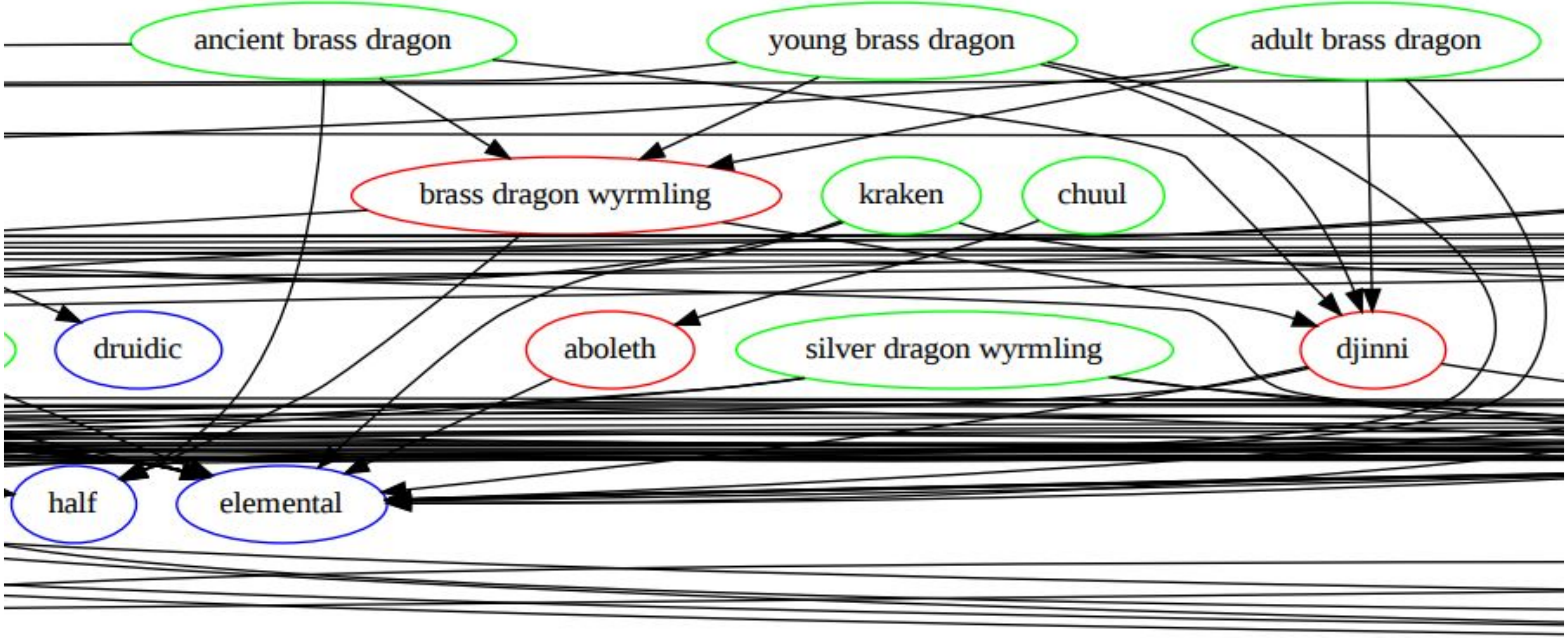
Monster Entity Extraction

Model	Training	Precision		Recall		F1	
		Text Lookup test data	Manually tagged test data	Text Lookup test data	Manually tagged test data	Text Lookup test data	Manually tagged test data
FLAIR Config 1	Setup 1	62.11	82.97	72.46	28.23	66.89	42.12
	Setup 2	91.91	85.58	92.46	89.17	92.19	87.34
FLAIR Config 2	Setup 1	64.91	86.10	80.43	28.58	71.84	42.87
	Setup 2	91.11	85.47	**92.87**	**89.50**	92.97	87.43
Trankit	Zero shot	0.00	0.00	0.00	0.00	0.00	0.00
	Setup 1	66.42	82.58	65.94	26.78	66.18	40.44
	Setup 2	**96.67**	**86.44**	92.26	89.33	**94.42**	**87.86**

Monster Entity Extraction

```
Text Lookup ancient blue dragon:['blue dragon', 'devil', 'air elemental', 'verdant',
                                 'brass dragon', 'bard', 'wizard', 'assassin', 'ankheg', 'giant scorpion', 'noble']
Trankit tag ancient blue dragon:['blue dragon', 'dust devil', 'air elemental', 'verdant',
                                 'brass dragon', 'minion', 'bard', 'wizard', 'assassin', 'ankheg', 'giant scorpion', 'noble']
Text Lookup ice devil:['ice devil', 'devil', 'pit fiend']
Trankit tag ice devil:['ice devil', 'devil', 'fiend', 'archdevil']
Text Lookup blood hawk:['blood hawk']
Trankit tag blood hawk:['blood hawk']
Text Lookup cultist:['cultist', 'elemental', 'acolyte']
Trankit tag cultist:['cultist', 'elemental', 'acolyte']
Text Lookup bandit:['bandit', 'thug', 'veteran', 'banditry']
Trankit tag bandit:['bandit', 'thug', 'veteran', 'banditry', 'pirate']
Text Lookup flying snake:['flying snake', 'cultist']
Trankit tag flying snake:['flying snake', 'cultist']
```

Monster Entity Extraction



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