FindHer: a Filter to Find Women Experts

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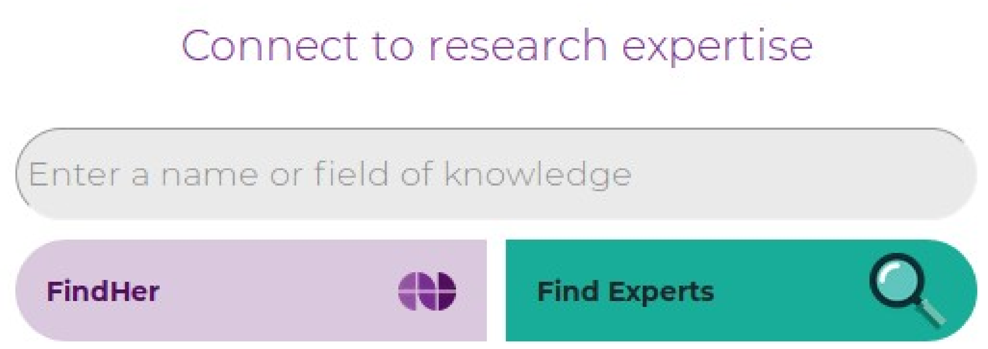
Motivation

Gender inequality persists globally. Considerable investment is now being channeled into raising awareness of biases, challenging inequitable systems and catalysing change. Whilst necessary, efforts may require significant manual effort from women or be heavily duplicated and investments made without proper evaluation of what already exists and what is working.

Expert Connect is a searchable database of Australian research expertise which has been drawn from exiting public sources of data to produce an open, automatically updated directory. **FindHer** was developed to help elevate the discovery of women in **Expert Connect**. In the absence of clear gender tagging, it is necessary for **FindHer** to infer gender from a number of indicators present in existing public data.

Goal

Evaluation of Natural Language Processing and Computer Vision technologies for automating gender determination for profile tagging for **ExpertConnect**



Gender determination methods

- **Title lookup**
  - One or more words prefixing peoples names: Mrs, Dr, President, etc.
  - Assigned the gender associated with the title as the user's gender
- **Name lookup**
  - Use names directories: '*500 women scientist*', '*Woman in science Australia*' with 150 female names
  - Assigns the gender associated with the name found in a list as the user's gender
- **Genderize**
  - Use big datasets of information from user profiles across major social networks across 79 countries and 89 languages
  - Assigns gender associated with the highest frequency count estimate
- **Chicksexer**
  - Character based multi-layer classifier LSTM network
  - Assigns the gender associated with the highest probability estimate
- **Facifier**
  - Supervised classifier gender determination using images
  - Trained with 6900 images
  - Assigns the gender associated with the highest probability estimate
- **CNN-Gender**
  - Convolutional Neuronal Networks for gender determination using images
  - Trained with 26,580 images
  - Assigns the gender associated with the highest probability estimate

Experiment Results

Table 1. Title and Name lookup results

	Title lookup	%
Ms.	1	0.03
Mrs.	8	0.25
Miss	0	0
Sister	0	0
Total females	9	0.28
Mr.	19	0.60
Dr.	322	10
Prof.	66	2
	Name lookup	**%**
Females	64	11

- **Lookup** methods have poor coverage
- Small percentage of **Expert Connect** profiles includes a title
- Catalogs are usually incomplete

Table 2. Off-the-shelve gender determination methods results

	Precision	Recall	F1
Chicksexer	0.982	0.876	0.925
Genderize	0.925	0.901	0.912
Facifier	0.421	0.738	0.534
CNN-gender	0.933	0.861	0.895

Table 3. Evaluation data set for names and images

	Female	Males
Names	568	263
Images	3934	3147

- **Chicksexer** and **Genderize** achieved high precision and recall
  - Unisex names, e.g.: *Sasha*, *Alex*, *Ali*
  - Short versions of names, e.g.: *Cat*, *Steph*, *Nicky*, *Charlie*
- **Facifier** struggles the face in images, and it's not able to predict the gender class
- **CNN-gender error analysis**
  - Many women with short hair and glasses are missclassified
  - Persons appearing at a corner of the image are usually missclassified

Limitations and Ethical Considerations

- In **Expert Connect**, people have a profile irrespective to gender
- Gender is seen as an spectrum, rather than a binary way
- Names and images do not unambiguously the gender of a user
- Users might not identify with the prototypical gender they look alike nor with their given name

Conclusion and Future Work

- The assessed methods are successful, and performance is likely to be higher if name-based and image-based methods are combined.
- For the future, we want to re-train name methods using culturally diverse set of names

FOR FURTHER INFORMATION

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LINKS

https://expertfindher.global/
https://expertconnect.global