WHERE ARE THE WOMEN ENTREPRENEURS?

A Case Study on Standard Chartered's SocialAI Model to Identify Women-Owned SMEs in Bank Portfolios

In 2022, Standard Chartered, a leading international cross-border bank headquartered in London with a presence in over 50 of the world's most dynamic markets, took a bold step to advance gender equality. Following years of work focused on elevating women in its workforce, the bank developed a program, the Women's International network (SC WIN), to elevate women entrepreneurs as clients. With the launch of SC WIN, Standard Chartered embarked on a journey to strengthen its product offerings for women entrepreneurs country-by-country. Today, SC WIN is present in India, Kenya, Malaysia, Singapore, Hong Kong, Vietnam and Pakistan. The program has facilitated nearly USD 300 million worth of additional financing to women-owned SMEs (as of October 2024), with approximately double year-over-year financing growth and threefold year-over-year client growth.

Many banks on similar journeys to elevate women entrepreneurs struggle to segregate women-owned and led small and medium businesses ("WSMEs") as a distinct segment, as the banks do not have the data (and therefore the resulting analytics) to understand how women entrepreneurs can be best served. Even when banks update systems to capture sex-disaggregated data for new clients, they often face the much larger hurdle of how to identify women-owned businesses in their existing portfolios. For Standard Chartered, the question became, how could it overcome these challenges to segment existing WSME clients around the world without an exhaustive and expensive new data collection exercise?

In 2023, Standard Chartered deepened its commitment to social sustainability and appointed Natalie Marko Nietsch as its inaugural Global Head of Social Sustainability. In partnership with her team, the Sustainability Data team has piloted an innovative and multifaceted approach to enable the bank to disaggregate its SME portfolio by sex on a current and continuing basis, with over 90% accuracy, without the collection of private personal data. The team developed the Standard Chartered SocialAI model, a hybrid approach to identify whether enterprise owners are male or female using the first name, country-adapted, and public and internal datasets. Its model is flexible enough to be deployed across its global banking network, and simple enough to inform other banks looking to do something similar.

This Case Study, targeted to Financial Service Providers, aims to provide an overview of the model Standard Chartered has deployed, including the processes for developing such a model, the challenges encountered, and potential business implications. The Case Study and the associated technical materials are being shared as part of Standard Chartered's commitment to the WE Finance Code (the "Code"). It also includes a technical note and a link to the open code developed by Standard Chartered, which can be adapted for use by other financial institutions (to be shared soon).

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The Benefits Of Sex-Disaggregated Data Collection

Sex-disaggregating data is essential for Financial Service Providers (FSPs) to better understand and serve the WSME segment. In the financial services industry, data allows companies to estimate the size and growth of market segments, and to understand their behavior and characteristics. An intentional analysis of the women entrepreneurs market is critical to create tailored products and services, to develop strategy based on performance and profitability of different segments, and to understand how to market to groups of customers. For an FSP, the benefit of high-quality sex-disaggregated entrepreneur data is two-fold. First, an FSP can expand its customer base among women entrepreneurs in lending, investing, or banking services, and improve their own bottom lines (see ABN AMRO 2022; Women's World Banking 2020). FSPs can also meet corporate citizenship or social sustainability goals by helping to promote financial inclusion for women entrepreneurs, who are crucial to equality within societies, to economic growth, and to innovation.

Sex-disaggregated data is also useful for policymakers and regulators looking to encourage greater financial inclusion of women-owned and led businesses. Regulators can use global and national data to establish baselines to understand how much financing is going to women and women entrepreneurs. Sex-disaggregated data also helps them to assess whether their financial inclusion strategies are working and where constraints and bottlenecks remain. As a result, FSPs that invest in equitable data systems, including those that sex-disaggregate data, may be able to access pools of development or sustainable investment capital.

FSPs that collect sex-disaggregated SME data are typically driven by an internal business case, social and equality mandates, targeted WSME programs supported by investors or development finance institutions, or regulatory incentives.

Why Standard Chartered Focused On Sex-Disaggregating Its Data

As of 2024, Standard Chartered has a presence in over 50 markets worldwide, with over 85,000 employees in 650 branches servicing over 10 million clients. With a history that stretches back 170 years, the bank has a unique geographical footprint that connects Asia, Africa and the Middle East to each other and to global markets. The bank describes its business as connecting "the world's most dynamic markets, serving the businesses that are the engines of global growth and supporting people to meet their ambitions. Every day, we help clients to manage and invest their finances safely and seamlessly, and grow their businesses and wealth with confidence, as inspired by our brand promise, here for good."

Standard Chartered is widely recognized for its ambitious sustainability objectives. The bank aims to mobilize USD 300 billion in sustainable finance by 2030, is working across its business and functions to operationalize its target of reaching across net zero in its financed emissions by 2050 and is applying its innovative mindset to fund new ways to drive economic inclusion and unlock the areas where capital is not yet flowing at scale. This reflects Standard Chartered's commitment to delivering sustainable, inclusive growth and prosperity for the places it calls home.

Gender equality and inclusion have long been part of this sustainability vision. In 2016, Standard Chartered signed the UK HM Treasury Women in Finance Charter, pledging to have women occupy 35% of senior leadership roles by 2025. It also has received an EDGE Certification for its work on sex equality and takes part in the Bloomberg Sex-Equality Index. Data, analysis, and reporting are crucial to these workplace initiatives, which seek to include more women in decision-making in the financial sector.

The bank recognized that achieving all its sustainability goals depended on precise, actionable data. Accordingly, in 2022, a comprehensive Pan-Bank Sustainability Data Strategy was put in place to address data challenges and enhance the bank's ability to identify and capitalize on opportunities, particularly in underserved segments, including women entrepreneurs. This data-driven approach is seen as crucial for identifying opportunities to serve a diverse client base, to accelerate sustainable finance growth, and maintain a balanced risk profile. As part of its Sustainability Data Strategy, Standard Chartered prioritized sex-disaggregated data capture.

Standard Chartered's actions were built on an internal business case by the Social Sustainability team – the bank acknowledged that accurate tagging of women entrepreneurs, allowing better analysis of sustainable finance revenue and assets, would be crucial to drive its sustainability agenda.

Challenges In Collecting High-Quality Sex-Disaggregated Data

As Standard Chartered implemented its sustainability strategy across its global subsidiaries, the bank faced a number of data challenges. These ranged from diverse data protection and privacy regulations across countries to vast differences in data collection practices in each country of operation. On the operational side, Standard Chartered faced three main challenges in disaggregating data by sex. First, categorizing the bank's existing portfolio by the sex of the business owner was extremely difficult, as this information had not been collected when the bank initially established relationships with customers or potential customers. Second, the bank needed to determine an appropriate definition of what constitutes a woman-owned business. Finally, it faced the challenge of developing one solution for both new and existing customers that would be replicable across various geographies and cultural contexts.

Standard Chartered executives were not alone in realizing that their systems needed to change. Few banks can systematically identify women entrepreneurs or women-run companies in their portfolios, whether they are sole proprietors or women-led SMEs with multiple owners (World Bank Group 2020; GBA and Data2X 2018). Despite the significant benefits that such data could provide to promote financial inclusion, foster equitable economic growth, and expand markets served by FSPs, such data remain scarce.

Many FSPs encounter internal challenges when categorizing customers by sex (GBA, Data2X, and IDB 2019). In most cases, internal bank data collection systems are designed to disaggregate information by product type. When management information systems allow for segmentation analysis, it is rare that demographic factors like sex or age have been tagged. As a result, any decision to collect sex-disaggregated data requires new enhancements to internal systems, which require financial investment and employee time.

Even when efforts are made to collect sex-disaggregated data, quality can be poor (CGAP 2022). There are often challenges related to the definition of what constitutes a women-owned or women-led business. An FSP may find it straightforward to identify the sex of a sole proprietor, but the process becomes more challenging for any SMEs with multiple owners or chief executives. According to some definitions, an enterprise may be categorized as a WSME based on either the ownership structure or the management roles within the firm. More broadly, the absence of nationally accepted definitions for terms like «women-owned» or «women-led» can create inconsistencies in the data collected over time, or by different financial institutions within the same country, or by operations in different countries. This lack of standardization also makes it difficult to build comparable national datasets and draw meaningful insights.

Beyond inconsistent definitions, socio-cultural factors also affect the data collection. For example, ownership shares may not accurately reflect whether a woman genuinely controls an enterprise registered in her name or conversely if she effectively runs a business formally registered in, for example, her husband's name. These challenges underscore the need for locally informed definitions and robust verification processes to ensure that the data collected is accurate and reflects local customs and realities.

If FSPs do not currently tag their clients by sex, they typically need to define what will be counted as a woman-owned business and then develop methodologies to tag both existing clients and new clients (also see ADB 2023) as male or female. For new applicants, they should establish systems to categorize individuals who are owners or senior managers of SMEs, ensuring sex-specific data is collected from the outset. For existing clients, FSPs must develop a methodology to retroactively disaggregate data within their existing client databases, allowing for a comprehensive understanding of their current portfolios. These tasks can be daunting and time-consuming, but machine learning technology can be leveraged to predict whether business owners are men or women without requiring additional manual inputs, significantly reducing the effort involved.

How Standard Chartered Addressed Data Collection Challenges

As a first step, Standard Chartered introduced an optional field during the onboarding process for new clients, allowing the voluntary collection of data on whether enterprise owners are men or women, while respecting client privacy and preferences. This optional field was designed to accommodate sensitivities in different countries regarding data collection, balancing the need for privacy with the goal of better understanding and supporting women-owned businesses. Roughly 25% of clients voluntarily disclosed this data.

> **Standard Chartered also adopted a universal definition for a woman-owned business: At least 51% of shares are owned, operated, and controlled by one or more women; or at least 20% of the shares are owned by one or more women, with key decision-making and legal representation by a woman. This is consistent with the majority of global standards.**

With these parameters in place, Standard Chartered leveraged fully public, open-source technology to approximate whether the existing owners of a set of SME clients were male or female. This has allowed the bank to then determine if the company was likely women-owned (following its definition) and then identify, with a high degree of confidence, the WSME part of its lending book.

Now, with this extra data parameter, lending behavior data could be sex-disaggregated, so that the bank could better understand unique characteristics and performance of its women-owned business customers. To ensure that all data is handled with the care and in compliance with data protection regulations, strict guidelines are put in place internally as to who can see this data. Through this balanced approach, Standard Chartered is prioritizing its intention for equal access to lending in its business practices, while upholding high standards of privacy and security.

Components Of The Standard Chartered SocialAI Model

The Sustainability Data team that developed the Standard Chartered SocialAI model used a hybrid approach to identify the likely sex of enterprise owners using the first name, country-adapted and internal datasets. It is a custom-built model that enabled the bank to gain insights into its existing portfolio of clients to better serve client needs without additional data collection. The model integrates multiple modules and machine learning algorithms into a unified framework of prediction to achieve a better performance than a single process could have. The SocialAI model is capable of predicting with 90% accuracy, without relying on any actual sensitive personal data.

Implementing the model required significantly more effort compared to a typical AI/ML project, encompassing aspects such as data approval, personal data impact assessment, and responsible AI. The most challenging hurdle was obtaining data approvals, as the data was considered part of personal data even though it couldn't be traced back to an individual. Numerous approval queries to other teams within the bank focused on ensuring proper customer consent, data and process management to prevent issues related to process integration, predictive nature, and gender discrimination.

The SocialAI model is highly configurable and allows detection via a process that includes using 1 digit in national ID and name database lookup. Specifically, the SocialAI model leverages integration of name datasets, Bidirectional Long Short-Term Memory (Bi-LSTM) deep neural network and ID specifiers for detection and prediction based on the person's first name and country, which improves the model's prediction power and accuracy[1]. By default, the

[1] Standard Chartered incorporated ideas and part of the codes from the existing python libraries:

chicksexer, MIT license, https://github.com/kensk8er/chicksexer
namesex, GPL-3.0 license, https://github.com/hsinmin/namesex
name-dataset, Apache-2.0 license, https://github.com/philipperemy/name-dataset

model either detects information from 1 digit from IDs if available or performs a name lookup in databases (providing statistical results) and predicts the sex of an enterprise owner using the AI model. The output provides a prediction for each individual (e.g., female or male) along with the confidence level.

The SocialAI model includes four major components:

(See Appendix for more detail)

1. **Name Database with Lookup Module:** This module takes an individual's first name and country as input to query databases, which forms the basis for making sex predictions.
2. **Name Sex Prediction Using Machine Learning:** The SocialAI model applies two algorithms to encode names as numerical vectors specific to each country. This step leverages deep learning (bi-LSTM) and NLP techniques (text tokenisation and embedding), utilising both character-level and token-level features to predict sex based on name and country.
3. **Special Feature Module:** This component uses additional information, such as specific digits embedded in national IDs that indicate the sex of an individual. This applies in countries where national IDs include such indicators.
4. **Rule Engine:** A configuration module that defines the priority order of detection/prediction results from the three modules. For example, ID-based results take the highest priority, followed by database lookup, and finally, name prediction.

Standard Chartered is the first global signatory of the WE Finance Code, a leading initiative that brings together private and public sector stakeholders to close the financing gaps for women entrepreneurs through commitments to Leadership, Data, and Action.

Lessons Learned From Deploying The SocialAI Model At Standard Chartered

The development of the SocialAI model at Standard Chartered provided the bank with new insights into the complexities and challenges of using machine learning to produce sex-disaggregated data in a global banking context. Standard Chartered gained a deeper understanding of the intricacies involved, especially when deploying these models across diverse regions. This experience highlighted the importance of legal compliance, data quality, tailored approaches, and fairness in building models that are accurate and ethically sound in different cultural settings.

One key lesson learned was the **variability in prediction accuracy across different countries.** This variation was primarily driven by cultural, linguistic, and naming conventions unique to each region. These differences highlighted the difficulty of applying a uniform data model globally and emphasised the need for region-specific adaptations to improve accuracy. For example, "Kiran" and "Amit" are traditional male names in India, while they might be sex-neutral in the West and Middle East. "Amit" is predominantly masculine, meaning "infinite" or "Limitless" in Hindi and Sanskrit, while it is more neutral in Hebrew, meaning "Friend" or "companion". The situation is similar for the Malay name "Zulkifli" and "Khairul" (usually male) or "Nurul" and "Zulaikha" (usually female). As some names are not common in the global West, the general-purpose predictor without country-specific databases cannot provide a high-confidence answer.

Continue to enhance existing open-source libraries for sex prediction using names and nationalities to navigate legal, ethical, and technical challenges.

Another key takeaway was the **critical importance of legal compliance in data usage.** Not all public datasets are legally permissible for projects, making it essential to conduct thorough legal reviews and, where necessary, to create internal datasets that comply with all relevant regulations. Ensuring that data acquisition teams are well-versed in data compliance and intellectual property rights is essential to avoid legal pitfalls.

Develop a protocol for regular legal reviews of data sources and ensure a well-trained team to avoid legal issues. If external data sources pose legal risks or are not adequately licensed, consider using or creating an internal dataset that complies with all legal requirements.

The project also revealed the **importance of data quality.** Large datasets often contain errors, such as incorrect labels, or may include duplicate entries from various sources. The quality of the data for some internal non-mandatory data fields can also vary and be of lower quality. These issues highlight the need for rigorous data cleaning and pre-processing stages to ensure the accuracy and reliability of the data used by the model. Quality control measures, including sample checks and removing duplicate entries, are critical for maintaining the integrity of the dataset.

Establish routine data cleaning to handle inaccuracies and duplications, train data teams on quality assurance methods and tools, and develop a comprehensive processing toolkit based on internal business characteristics and the logic of the model.

Another significant lesson learned was the **challenge of training the model and validating the results.** Variations in data distribution between training and testing can result in performance inconsistencies, particularly due to the significant differences in naming conventions across countries. For example, some names have a small number of characters (e.g., names based on the Latin alphabet), while others, like Chinese, Japanese, or Korean names, may consist of a larger number of characters. Since the SocialAI model is applied across multiple countries where Standard Chartered operates, the development process highlighted the need for advanced techniques, such as k-fold cross-validation and domain adaptation, to ensure consistent performance across different data subsets. Moreover, it became clear that different naming conventions require different approaches. For instance, character-level features may work well for names of Latin origin, while languages with complex character sets, such as Chinese or Japanese, benefit more from token-based vector methods. This insight led to the development of a modular AI system, allowing preprocessing and feature extraction techniques to be tailored to the specific characteristics of the input data.

Design and merge datasets to ensure they cover a wide and representative population. Techniques such as k-fold cross-validation and domain adaptation are important to ensure the model performs well across diverse data subsets. Using a shuffled train-test split can be further beneficial to fine-tune the model. Using hybrid methods for different types of names is recommended when there is a large variability in names. Perform continuous research and development to refine methods based on linguistic and cultural nuances.

The Standard Chartered team also had to decide **how to handle imbalanced datasets.** The data often exhibited inherent imbalances in the Standard Chartered datasets, with ratios of female to male data varying significantly across different countries. In some countries, the ratio of female to male could be as large as 20% to 80%, leading to significant disparities. This imbalance can create issues in developing AI models, as algorithms might become biased toward the majority group, resulting in inaccurate predictions or unfair outcomes. For example, if the data heavily favors one sex, the model may struggle to make reliable predictions for the underrepresented group. To address this, the team implemented techniques like resampling, where data from the underrepresented group is duplicated or the overrepresented group's data is reduced to create balance. They also explored advanced methods such as algorithmic adjustments to ensure fairness, like weighting the data to give more importance to the underrepresented group. These efforts ensured that the AI models could deliver fair and reliable outcomes, even with skewed data distributions.

Implementing robust evaluation metrics that specifically measure performance of the AI model in imbalanced scenarios is crucial, along with continuous monitoring and adjustments to refine AI model performance in such cases.

Finally, the project underscored **the importance of fairness and inclusivity.** To avoid biases and improve accuracy across diverse demographic groups, the model had to incorporate a wide range of naming conventions from various cultures. The built-in transparency in the model's decision-making process was an important step that allowed Standard Chartered to understand how predictions were made and allow the assessment of potential biases. This transparency, combined with the intentional inclusivity in data collection, enhanced the model's utility and fairness in global applications.

Strategically select fairness metrics, such as equal opportunity or predictive parity, in evaluating the fairness of systems. Choose metrics that align with the project's specific ethical and operational goals. Additionally, define an acceptable range of fairness to guide model adjustments and ensure the AI system treats all groups equitably.

Advancing The Field: The Decision To Make The SocialAI Model Public

The Role of the WE Finance Code Commitment

Standard Chartered became the first global signatory of the WE Finance Code (the “Code”) in 2023, shortly after the Code was launched at the World Bank-IMF Annual Meetings in Marrakech, Morocco by the Women Entrepreneurs Finance Initiative (“We-Fi”). The Code is a commitment by FSPs, regulators, development banks and other financial ecosystem players to support women-led micro, small and medium-sized enterprises, so they can grow and add value to their communities. Signatories commit to three actions:

As part of its commitments to the Code, Standard Chartered agreed to share its SocialAI model with We-Fi so that Code signatories in the peer bank community could learn from its experiences. We-Fi reshares Standard Chartered’s model on the Women Entrepreneurs Finance Initiative website so other banks can evaluate if this type of solution suits their needs. The bank hopes that by sharing these types of experiences and solutions with other Code signatories, other FSPs facing similar sex-disaggregated data challenges can evaluate similar solutions so that financing to women-owned and women-led businesses can grow.

How Other FSPs Can Learn from Standard Chartered’s SocialAI Model

Standard Chartered designed its SocialAI model to be highly customisable, which means that other banks and financial institutions can replicate or adapt it to their own needs and datasets. When evaluating if the model could work for their bank, other FSPs can use prepare their own a training dataset based on names commonly used in their respective countrie. Standard charted will also share the model library and technical notes so that other banks can get started to train their own model more easily. FSPs looking to adopt this approach can customise the model based on the provided key logic. This includes:

- (a) looking up names in an existing database to identify sex of enterprise owners with set probabilities,
- (b) using pre-developed models to train and predict sex of enterprise owners based on different character sets (e.g., Latin, or Chinese), and
- (c) extracting sex of enterprise owners from national IDs based on specific digits, where applicable. However, this option may not be available in all countries.

Leadership: Designate a member of their senior management team to champion the organization’s efforts to support women-led businesses.

Action: Expand and introduce new measures that will support women entrepreneurs.

Data: Monitor and report annually on an agreed-upon set of indicators on the level of financing provided to WMSMEs, or support others’ efforts to do so.

ENDNOTES

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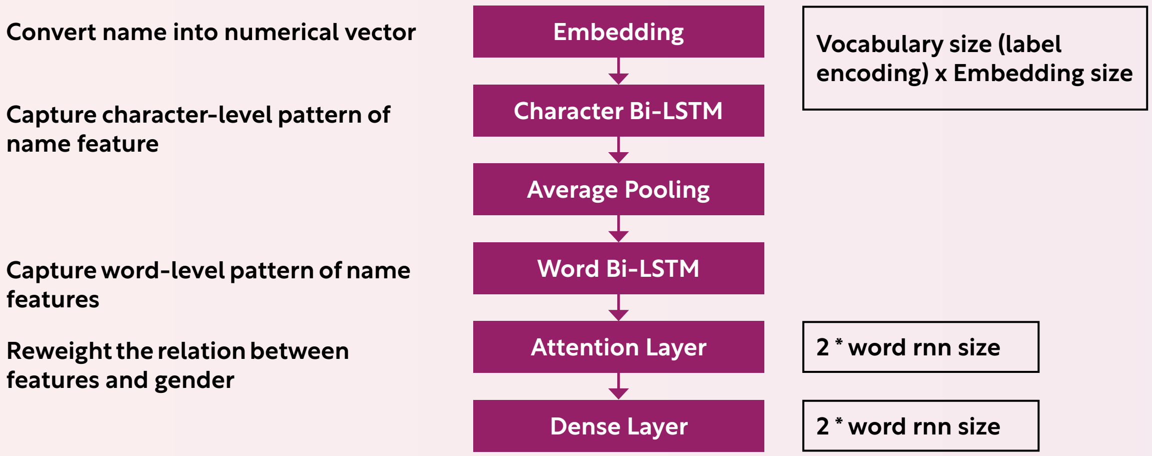
ANNEX

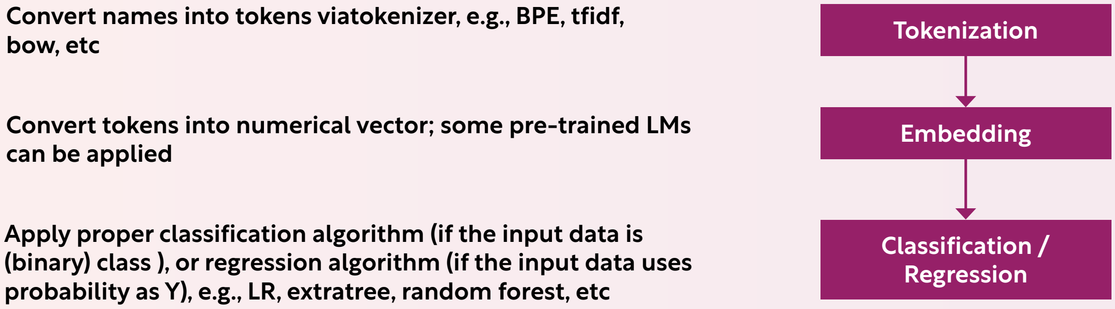
Algorithm 1: bi-LSTM (bidirectional Long-Short Term Memory)

The deep learning bi-LSTM model captures the pattern of the names regarding sex in both character-level and word-level. This algorithm can be applied to Latin-like characters.


Convert name into numerical vector
Capture character-level pattern of name feature
Capture word-level pattern of name features
Reweight the relation between features and gender
Embedding
Character Bi-LSTM
Average Pooling
Word Bi-LSTM
Attention Layer
Dense Layer
Vocabulary size (label encoding) x Embedding size
2 * word rnn size
2 * word rnn size

Algorithm 2: Natural Language Processing NLP (text tokenization and embedding techniques)

The Natural Language Processing NLP text tokenization and embedding algorithm applies a tokenizer to separate the name string into tokens and convert them into vectors (embeddings). The users can employ the pre-trained (language) embedding models (e.g., word2vec) or train their own language models with the predefined format and sufficient corpus. Once the vectors are obtained, the users can apply any classification (if binary labels)/regression (if probability labels) algorithms to predict the sex. In the code, we provide a random forest-based algorithm with combined vectors of embedding and word counters as features.


Convert names into tokens viatokenizer, e.g., BPE, tfidf, bow, etc
Convert tokens into numerical vector; some pre-trained LMs can be applied
Apply proper classification algorithm (if the input data is (binary) class), or regression algorithm (if the input data uses probability as Y), e.g., LR, extratree, random forest, etc
Tokenization
Embedding
Classification / Regression

ANNEX

A unified framework for sex prediction works better than single processes to achieve a better performance. A unified model combines all three algorithms to address the shortcomings of each individual module.

Module/Algorithm	Functionality	Pro	Con
ID Specifier	Provide the exact sex information directly based on the (national/resident) ID number (either the full number or the specified digits)	Simply rule-based; highly accurate when based on authoritative data	Limited to countries where such IDs encode sex; not universally applicable.
name database lookup	Identify sex by referencing statistical databases of names	Simple and effective for names present in the database	Only applicable to existing names in the database, whose size and coverage can vary
ML - character-based	Predict the sex based on the (first) name using the model trained with self-contained character-level features	Able to predict any names theoretically; able to train the model without language model dependency	Performance may decline with longer names or unknown characters due to feature extraction limitations.
ML - token-based	Predict the sex based on the (first) name using the model trained with pre-trained embeddings	Able to predict any names theoretically; applicable to process the names with very large number of characters, e.g., Chinese	Dependent on the quality and relevance of the pretrained language model.