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Master's thesis

Data Selection Strategies for Multi-Speaker Text-to-Speech Synthesis in Lithuanian

Work Title in Lithuanian

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Introduction

The goal of creating machines that can speak like humans has captivated researchers for centuries. One of the earliest known attempts dates back to the 18th century, with Wolfgang von Kempelen's mechanical speech machine that utilized a bellows-driven lung and physical models of the tongue and lips.

Over the centuries, advancements in technology and understanding of human speech have driven significant progress in this field. Today's state-of-the-art systems, dominated by end-to-end (E2E) neural models, have achieved highly naturalistic speech with unprecedented acoustic quality. Notably, these end-to-end systems have unified the entire synthesis process into a single neural network, eliminating the need for complex multi-stage pipelines.

Training high-quality TTS models typically requires large amounts of annotated speech data. The common recommendation is to use at least 10 hours of recorded speech from a single speaker to achieve good results.

Liepa 2 is a recently released Lithuanian speech corpus that contains 1000 hours of annotated speech; however, this data is distributed across more than 2600 speakers, with most speakers contributing only a few minutes of speech. The top speaker has around 2.5 hours of recorded speech.

Training a high-quality single-speaker TTS model on such limited data poses a challenge. Multi-speaker TTS models can utilize data from multiple speakers to improve performance. However, training on all available data is a time-consuming and computationally expensive process, especially in the context of a master's thesis.

Therefore, it makes sense to explore strategies for selecting smaller subsets of the available data for training. The question that arises is, what is the best way to sample multi-speaker data for training TTS models?

This thesis aims to answer the following research questions:

- TODO

Scope: This study is exclusively focused on the Lithuanian language and the Liepa 2 speech corpus. It investigates a fixed total training data size of 30 hours. The models are limited to Tacotron 2 with DDC and FastPitch architectures within the Coqui TTS framework, using a pre-trained WaveGlow vocoder for waveform generation.

Limitations: The findings may not generalize to other languages, datasets with different characteristics, or other TTS architectures. The 30-hour training data size is a practical constraint and may not reflect performance at larger scales.

1 Literature review

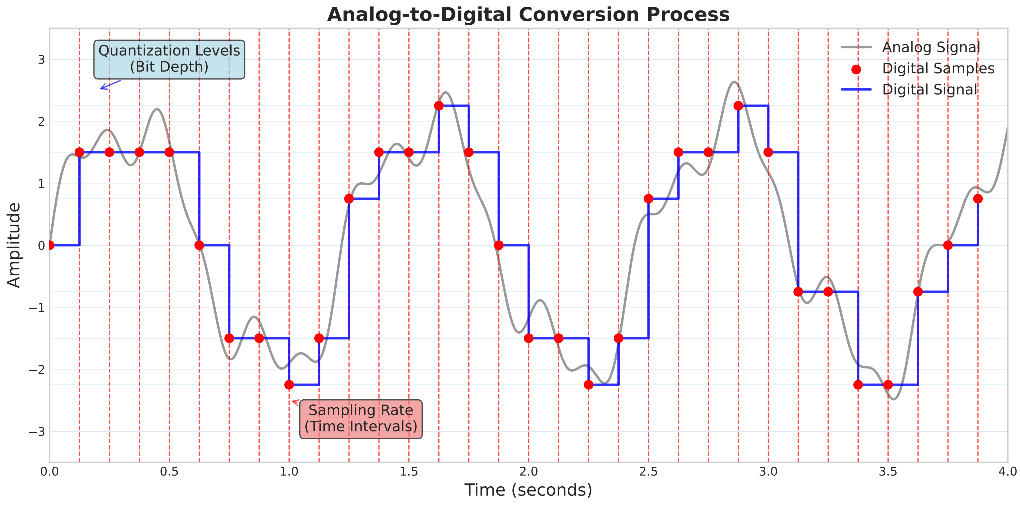
1.1 Digital representation of audio

Speech, or sound in general, is a continuous pressure wave that propagates through a medium, such as air. The key properties of sound waves include frequency (pitch), amplitude (loudness), and phase.

Converting continuous sound waves into a digital format suitable for computer processing involves two main steps: sampling and quantization.

Sampling is the process of measuring the amplitude of the sound wave at regular time intervals. The rate at which these samples are taken is called the sampling rate. According to the Nyquist-Shannon [16] sampling theorem, accurate reconstruction of a continuous signal requires a sampling rate that is at least twice the highest frequency present in the signal. The majority of human speech information is concentrated between 100 Hz and 8 kHz. [15] Thus, in text-to-speech applications, common sampling rates for audio are 22.05 kHz and 24 kHz, which can capture frequencies up to approx. 11 kHz and 12 kHz, respectively.

Quantization (also known as bit depth) is the mapping of continuous amplitude values to discrete levels for digital representation. Typical bit depths for audio are 16-bit and 24-bit formats.



1 figure. *Visual representation of Analog-to-Digital conversion. The continuous grey line represents the analog signal. The vertical lines represent the* ***sampling rate*** *(time intervals), and the horizontal grid lines represent* ***quantization levels*** *(bit depth).*

Pre-emphasis is a high-frequency filtering technique applied to audio signals before further processing. Natural speech signals tend to have more energy in the lower frequencies, with a gradual drop-off towards higher frequencies (typically around -6 dB per octave). Pre-emphasis compensates for this spectral tilt by boosting high frequencies using a first-order high-pass filter, which is defined as:

$$y[n] = x[n] - \alpha x[n-1] \tag{1}$$

where $y[n]$ is the pre-emphasized signal, $x[n]$ is the original signal, α is the pre-emphasis coefficient (typically between 0.9 and 1.0), and n is the sample index.

This transformation balances the frequency spectrum, improving the signal-to-noise ratio for higher frequencies and preventing the model from optimizing only for low-frequency components.

1.2 Time-Frequency Analysis

1.2.1 Fourier Transform

Fourier Transform (FT) is a mathematical technique that transforms a time-domain signal (such as an audio waveform) into its frequency-domain representation. The signal is decomposed into a sum of sine and cosine waves at various frequencies, each with a specific amplitude and phase. This allows us to analyze the frequency content of the signal.

Short-Time Fourier Transform [14] (STFT) extends the FT by applying it to short, overlapping segments (frames) of the signal. This transformation provides a time-frequency representation, showing how the frequency content of the signal changes over time.

In TTS applications, the STFT is computed by dividing the audio signal into short frames (usually, 20-50 ms) with a certain overlap (usually, 50-75%) between frames, windowed by a Hamming or Hann function to minimize the spectral leakage.

1.2.2 Spectrogram and Mel-spectrogram

The spectrogram is a visual representation of the STFT, displaying frequency on the vertical axis, time on the horizontal axis, and amplitude represented by the color intensity.

However, the human ear does not perceive frequencies linearly — it is more sensitive to lower frequencies than higher ones. To mimic this perceptual characteristic, the Mel scale [20] maps linear frequency f (in Hz) to a perceptual scale m (in Mels) using the following formula:

$$m = 2595 \cdot \text{log}_{10}\left(1 + \frac{f}{700}\right) \tag{2}$$

Mel-spectrograms are computed by applying a Mel filterbank of overlapping triangular filters (or kernels) to the magnitude spectrogram obtained from the STFT. This results in a compressed representation of the audio signal that aligns more closely with human auditory perception. Such Mel-spectrograms are commonly used as input features for modern TTS systems.

2 figure. *Raw audio waveform (top), its spectrogram (middle), and Mel-spectrogram (bottom) representations.*

1.3 Text-to-speech synthesis

Text-to-Speech (TTS) synthesis, also known as speech synthesis, is the process of converting written text into human-like spoken words. Nowadays TTS is a key technology in numerous applications, including virtual assistants, accessibility tools, and language learning platforms.

1.3.1 Traditional TTS approaches

Early attempts at artificial speech synthesis evolved from the first mechanical devices in the 18th century to electronic systems. Wolfgang von Kempelen's mechanical speech machine demonstrated basic phoneme production using a physical model of the vocal tract. In 1937, Homer Dudley's invention of the Voder [10] became the first electronic speech synthesizer that could produce intelligible speech through operator-controlled acoustic parameters, establishing the foundation for modern electronic synthesis methods.

In the decades that followed, two main approaches for speech synthesis emerged: concatenative synthesis and parametric synthesis.

1.3.2 Concatenative synthesis

The concatenative synthesis approach [6] synthesizes speech by piecing together pre-recorded segments of human speech. This method involves several steps. First, it requires pre-recording a large database of speech segments spoken by a human voice actor in pristine, highly controlled studio conditions to ensure consistent audio quality and minimize background noise. Each segment is labeled and indexed based on its phonetic and prosodic properties.

During synthesis, the system breaks down the input text into short linguistic units (such as phonemes or syllables) using a text analysis module. Then, it queries the speech database to find the best-matching segments for each unit using selection cost functions [2]. The retrieved segments are blended and concatenated to form a continuous speech waveform. The system then uses signal processing techniques to smooth the transitions between segments and adjust pitch and duration to match the desired output characteristics.

Concatenative synthesis can produce natural-sounding individual speech units, but the final audio often has noticeable glitches and breaks at the points where segments are joined together [2]. The segments may not blend smoothly due to differences in pitch, duration, and timbre. The prosody also tends to sound “choppy” and unnatural, since stringing disjointed segments together does not capture the natural rhythm and intonation patterns of connected speech.

Finally, concatenative synthesis requires language-specific expertise to design and maintain the underlying speech database and selection algorithms. This need for extensive data can make it challenging to develop concatenative TTS systems for low-resource languages or dialects.

1.3.3 Parametric synthesis

In contrast, statistical parametric speech synthesis [25] (SPSS) uses statistical models, typically Hidden Markov Models (HMMs) [21], to generate the parameters that control a speech waveform.

This method involves training a statistical model on a large corpus of recorded speech. The model learns the relationship between linguistic features (like phonemes and prosody) and the acoustic features of the speech signal, such as spectral envelope and fundamental frequency. During synthesis, the system takes text as input, converts it to a sequence of linguistic features, and then uses the trained model to generate a corresponding sequence of acoustic parameters.

Compared to concatenative synthesis, the statistical approach allows for more flexibility and control over the speech synthesis process, enabling the generation of a wider variety of voices and speaking styles. However, HMM-based synthesis [21] had a persistent problem: the statistical averaging built into the models tended to over-smooth the acoustic features, creating a characteristic "buzzy" or "muffled" sound that lacked the sharpness and detail of natural human speech.

1.4 Linguistic Representation (Text Processing)

1.4.1 Text normalization

Text normalization [19] is the process of converting raw text into a standardized format suitable for TTS synthesis. Typical steps include expanding abbreviations (e.g., expanding "Dr." to "Doctor"), punctuation removal, number normalization (e.g., converting "123" to "one hundred twenty-three"), and lowercasing.

1.4.2 Graphemes vs. Phonemes

A key decision in TTS systems is the choice of input representation for text.

There are two main approaches, namely grapheme-based and phoneme-based. The grapheme-based approach uses the raw characters of the written text as input to the TTS model. This method is straightforward and does not require any additional pre-processing steps. However, it can struggle with languages that have complex orthographies or inconsistent spelling-to-sound correspondences.

In contrast, the phoneme-based approach uses a phonetic transcription of the text, typically in the International Phonetic Alphabet (IPA) format. The underlying assumption is that phonemes possess a more direct and consistent mapping to the acoustic features of speech, making it easier for the TTS model to learn the relationship between text and audio. However, this approach requires an additional grapheme-to-phoneme (G2P) conversion step [1], which requires a complex pre-processing pipeline or a separate G2P model.

There is another approach that augments the grapheme-based representation with accentuation marks. This method adds accent marks (typically tilde, acute, grave accents) to the raw grapheme sequence to indicate the stressed syllables in words. This additional information provides cues about the prosodic features of speech, which can help improve the pronunciation and naturalness of the synthesized speech.

1.4.3 Specific challenges in Lithuanian

Lithuanian is a Baltic language with a rich inflectional morphology and complex prosodic structure. It is a pitch-accent language with free stress, meaning the stress can fall on any syllable in a word, and can change the position depending on the grammatical form.

Challenges in Lithuanian TTS synthesis include:

- **High OOV rate:** Due to extensive word inflection, the number of unique word forms is significantly higher than in English. This leads to data sparsity issues where many valid word forms may not appear in the training set.
- **Ambiguity without accentuation:** Typically, stress marks are omitted in written Lithuanian. However, stress position and tone (acute, circumflex, or short) determine the meaning of monographic words. Examples are shown in Table 1 table.. A grapheme-based model without accentuation marks may struggle to predict the correct prosody, resulting in monotonic or mispronounced speech.

Word	Accentuation	Meaning
Antis	*ántis* (Acute) *añtis* (Circumflex)	A duck (noun) Bosom/Chest (noun)
Kasa	*kãsa* (Circumflex) *kasà* (Short)	He/she digs (verb) Braid/Pancreas (noun)

1 table. *Examples of Lithuanian homographs where accentuation determines meaning. A grapheme-only model cannot distinguish these without context or explicit stress marks.*

To overcome these challenges, tools like **Kirčiuoklis** (Vytautas Magnus University) are often employed in the text normalization pipeline. Kirčiuoklis automatically assigns stress marks to raw text. One weakness of Kirčiuoklis is that it relies on a word-dictionary based approach, which does not take into account the context of the word. Thus, it suggests multiple possible accentuation variants for ambiguous words, leaving it up to the user to select the correct one.

In the absence of a high-quality, context-aware Grapheme-to-Phoneme (G2P) converter for Lithuanian, this thesis will focus on grapheme-based TTS synthesis with accentuation marks provided by Kirčiuoklis. In cases where Kirčiuoklis suggests multiple accentuation variants for a word, no stress marks will be added, leaving the TTS model to infer the correct prosody from context.

1.5 Embeddings and Representation Learning

1.5.1 The Concept of Embeddings

In machine learning, embeddings are dense vector representations of discrete entities (such as words, characters, or speakers) to a high-dimensional continuous vector space. Unlike one-hot encodings, which are sparse and highly dimensional, embeddings provide a dense, lower-dimensional representation that captures semantic relationships between underlying entities. For instance, in word embeddings, similar words tend to have more similar (correlated) vector representations, while dissimilar words map to more distant points in the vector space.

1.5.2 Text Embeddings

The “Encoder” part of a TTS model is responsible for converting a sequence of input symbols (characters or phonemes) into a sequence of feature vectors. Typically, this is done using an embedding layer, which maps each input symbol to a learnable fixed-size vector representation. During training, these embeddings are learned jointly with the rest of the TTS model.

1.5.3 Speaker Embeddings

In order to enable multi-speaker synthesis, TTS models need to receive a representation of the speaker’s identity.

Lookup Tables (LUT): Early approaches used simple learnable embeddings where each speaker ID is mapped to a unique vector. The vectors are learned joinly with the TTS model during training. While efficient, this approach cannot generalize to speakers not seen during training.

Reference encoders and speaker embeddings:

3 figure. *General architecture of a Speaker Encoder. A reference audio of arbitrary length is processed (typically by LSTM or TDNN layers) and pooled to produce a fixed-length embedding vector (e.g., d-vector) representing the speaker identity.*

Transfer learning approaches [8] have demonstrated adapting speaker verification models to multispeaker TTS synthesis, enabling better speaker adaptation and higher voice quality. A speaker encoder model pre-trained on a massive, noisy dataset with thousands of speakers (such as VoxCeleb) learns the general speaker space. Its pre-trained weights are then frozen and used to extract embeddings for the TTS training data, allowing the TTS model to effectively account for multi-speaker characteristics.

d-vectors: d-vectors [22] are fixed-length speaker embeddings derived from a separate speaker verification model. A reference encoder network takes a reference audio recording of arbitrary length and compresses it into a fixed-length vector known as a d-vector, that summarizes the speaker’s timbral and prosodic characteristics. These d-vectors are then provided as additional input to the TTS model, and are kept fixed during TTS training.

x-vectors: An evolution of d-vectors, x-vectors [18] use a more Time Delay Neural Network (TDNN) architecture to capture the temporal context more effectively. These embeddings have shown an improved ability in zero-shot TTS scenarios.

One limitation of d-vectors and x-vectors is that if the reference audio is of poor quality or contains background noise, the resulting speaker embedding may not accurately represent the speaker’s identity, leading to degraded synthesis quality.

1.6 Deep learning for TTS

The limitations of complex, multi-stage pipelines motivated the creation of a new approach, the end-to-end (E2E) model. E2E systems learn the entire speech synthesis process — from input text directly to acoustic output — using a single neural network. This approach promised to eliminate the need for hand-crafted pipelines that were difficult to design, required extensive expertise, and suffered from errors that accumulated across multiple components. By learning directly from text-audio pairs, E2E models showed they could produce speech with higher naturalness and expressiveness than previous methods, representing a significant leap in TTS technology.

However, although deep learning TTS models are more robust to variations in data quality compared to concatenative approaches, they are essentially "data-hungry" beasts that require large amounts of training data to achieve optimal performance. This relationship between model performance and training data size follows well-established scaling laws for neural models [9]. This characteristic makes data selection and quality control critical factors in developing effective neural TTS systems.

1.6.1 Feedforward neural networks

Feedforward Neural Networks (FNNs) are the simplest type of artificial neural networks, consisting of layers of interconnected nodes (neurons) where information flows in one direction — from the input, through hidden layers, to the output. While FNNs can be useful for basic regression or classification tasks, they lack the memory and context-awareness needed for processing sequential data like text and speech. Therefore, FNNs are not suitable for modelling TTS tasks that require understanding of temporal dependencies.

1.6.2 Encoder-Decoder architectures

The Encoder-Decoder architecture is a neural network architecture consisting of two components, namely an encoder and a decoder. The encoder processes the input data and compresses it into a high-dimensional latent representation. This vector captures the meaningful features of the input. The decoder uses this latent representation as context to generate the final output. This architecture is commonly used in sequence-to-sequence tasks, such as machine translation (text-to-text) and text-to-speech synthesis (text-to-audio frames).

1.6.3 Tacotron 2

A common approach for TTS modelling it the sequence-to-sequence (seq2seq) framework, which uses an encoder-decoder architecture with an attention mechanism to map input (text) sequences to output (audio) sequences.

This architecture has three main components:

Encoder: The encoder processes through the input text sequence (graphemes or phonemes) and converts it into a high-level representation. Typically, this is done using recurrent neural networks

(RNNs) or more complex modules like the CBHG (Convolution Bank + Highway network + Gated Recurrent Unit). **Attention Mechanism:** The attention mechanism learns to align the high-level text representation with the output audio frames. At each decoding step, it determines which part (positions) of the input text the model should focus (or “attend to”) in order to generate the next audio frame. **Decoder:** Finally, the decoder — also typically an RNN — takes the encoder output, uses the attention output as context, and generates an acoustic representation of speech (typically mel-spectrogram) frame by frame. Being autoregressive, the decoder is a “bottleneck” during inference, as it must generate each frame sequentially, only after the previous one has been produced.

4 figure. *The Tacotron 2 architecture. Note the recurrent connections in the decoder and the attention mechanism aligning encoder outputs to decoder steps. [17]*

Tacotron [24] and Tacotron 2 [17] are two notable TTS models based on the sequence-to-sequence architecture. The variant that this thesis primarily focuses on is Tacotron 2 with Double Decoder Consistency (DDC).

In Tacotron 2, the encoder consists of a character embedding layer, followed by a stack of convolutional layers (which encode local context about neighbouring characters), and a bidirectional LSTM. The attention mechanism is location-sensitive, computing an alignment between the encoder outputs (text) and the decoder steps (audio frames). The decoder is an autoregressive RNN, typically composed of LSTM layers.

1.6.4 FastPitch

5 figure. *The FastPitch architecture. It utilizes a feed-forward Transformer and an explicit duration predictor, allowing for parallel generation of the Mel-spectrogram. Pitch is predicted and injected into the latent representation. [13]*

Unlike Tacotron 2, FastPitch [13] replaces the recurrent layers with Transformer architecture blocks relying on self-attention. Being a non-autoregressive model, FastPitch model can process the entire input sequence in parallel, significantly speeding up both training and inference.

Unlike Tacotron 2, which learns alignment implicitly using attention, FastPitch requires an external aligner (or an internal alignment module) in order to determine how many sound frames correspond to each input character. A duration predictor network learns to predict these durations, ensuring the speech rhythm is stable.

FastPitch includes a dedicated predictor that estimates the fundamental frequency (F0) for every input symbol. The predicted pitch values are projected and added to the hidden states, allowing the model to explicitly control intonation before generating the spectrogram.

The primary advantages are inference speed (duet to non-autoregressive generation), robustness (no attention failures like skipping or repeating words), and controllability (pitch and speed can be tweaked manually during synthesis).

1.6.5 Notable End-to-End TTS models

Besides Tacotron 2 and FastPitch, other notable TTS architectures include **Glow-TTS**, which uses flow-based generative models for parallel inference, and **VITS** (Conditional Variational Autoencoder with Adversarial Learning), which combines the acoustic TTS model (Glow-TTS) with a neural vocoder (HiFi-GAN) into a single end-to-end architecture.

1.6.6 Neural vocoders

Standard TTS models like Tacotron 2 or FastPitch generate intermediate acoustic features (typically mel-spectrograms), but do not directly produce raw audio waveforms. However, mel-spectrograms are lossy representations that only capture the magnitude of the frequency bands, discarding phase information. This information is discarded during the STFT process. Thus, converting a spectrogram into audio is a non-trivial task, as the phase information must be estimated. This challenge is known as the *inversion problem*.

The tool used to convert spectrograms back into waveforms is called a vocoder.

Traditionally, the Griffin-Lim algorithm [5] has been used to iteratively estimate and reconstruct the phase information from the magnitude spectrogram. However, this method often produces audio with noticeable artifacts and lower quality compared to natural speech.

Neural GAN (Generative Adversarial Network) based vocoders, such as HiFi-GAN [11], have become the dominant approach for vocoding in modern TTS systems. These GAN-based vocoder models consist of two main components: a Generator, which reconstructs mel-spectrograms into raw waveforms, and a Discriminator, which distinguishes between real and synthesized audio. This adversarial training forces the Generator to produce high-fidelity audio that closely resembles natural speech.

The framework used in this thesis, Coqui TTS [3], comes with a pre-trained HiFi-GAN v2 vocoder trained on a large multi-speaker dataset (VCTK). Given its widespread adoption and status as a state-of-the-art neural vocoder, this thesis will use the HiFi-GAN v2 model for waveform generation. In order to ensure compatibility between the TTS models and the vocoder, the TTS models' acoustic parameters will be configured to the exact same settings (sampling rate, FFT parameters, Mel filterbank settings) as those used during the HiFi-GAN v2 training.

1.7 Multi-speaker TTS

Multi-speaker TTS models are designed to synthesize speech in the voices of multiple speakers. In order to achieve this, these models are trained on data from many different speakers, allowing them to learn the characteristics of each voice and synthesize speech that sounds like a specific individual, while still being able to generalize the shared linguistic and acoustic patterns across speakers.

1.7.1 Techniques

Techniques for multi-speaker TTS often involve conditioning the model on speaker identity. This can be done by providing a speaker embedding vector as an additional input to the model. Early successful implementations of this approach include Deep Voice 2 [4], which demonstrated effective multi-speaker synthesis by learning speaker-specific embeddings.

The speaker embedding can be learned jointly with the TTS model during training, or it can be pre-trained using a separate speaker verification model.

1.7.2 Challenges

One key challenge in multi-speaker TTS is ensuring that the model can effectively capture the unique characteristics of each speaker's voice while still producing natural-sounding speech.

The distribution of training data across speakers can also influence the model's performance and its ability to mimic all voices equally well. The training datasets are often strongly imbalanced, with some speakers having hours of annotated speech, while others may have only a few minutes. This imbalance can cause the model to overfit to the speakers with more data, resulting in lower synthesis quality for underrepresented speakers.

Thus, data selection and sampling strategies are critical considerations when training multi-speaker TTS models.

1.8 Data selection in TTS

As TTS models require large amounts of annotated speech data for training, training on all available data can be computationally prohibitive and time-consuming. Therefore, data selection aims to identify optimal subsets of the available data that can yield high-quality synthesis while minimizing training time and resource requirements.

1.8.1 Data quantity

The relationship between the quantity of training data and model performance in neural networks follows predictable scaling laws. Research by Kaplan et al. [9] showed that model performance generally improves as a power law function of the amount of training data, with diminishing returns at larger scales. Similar trends have been observed in TTS models, where increasing the training data size leads to better synthesis quality and naturalness, but with diminishing improvements as the dataset grows larger.

While this would suggest that "more data is better", in practice, collecting, curating, and processing large-scale multi-speaker TTS training datasets, as well as the computational burden of training on them, can be prohibitive. This makes efficient data selection strategies increasingly valuable for achieving optimal performance-to-cost ratios.

1.8.2 Data selection strategies

1.9 Evaluation methods for TTS

1.9.1 Subjective evaluation

TTS systems are often evaluated using subjective listening tests, where human listeners rate the naturalness and intelligibility of synthesized speech samples.

A common subjective evaluation method is the Mean Opinion Score [7] (MOS) test. In a MOS test, listeners are presented with a set of synthesized speech samples and are asked to rate each sample on a scale from 1 to 5. Here, the scale typically represents the following levels of quality:

- 1 - Bad: The speech is completely unnatural and unintelligible.
- 2 - Poor: The speech is mostly unnatural and difficult to understand.
- 3 - Fair: The speech is somewhat natural but has noticeable artifacts or issues.
- 4 - Good: The speech is mostly natural with minor artifacts that do not significantly affect intelligibility.
- 5 - Excellent: The speech is indistinguishable from natural human speech.

1.9.2 Objective evaluation

Objective evaluation methods use computational metrics to assess the quality of synthesized speech.

Common objective metrics include:

- Mel-Cepstral Distortion [12] (MCD): Measures the spectral distance between synthesized and natural speech.
- Fundamental Frequency Root Mean Square Error (F0 RMSE): Assesses the accuracy of pitch contours.

1.10 Summary

Modern TTS synthesis has evolved from complex, multi-stage concatenative and statistical pipelines to end-to-end deep learning architectures. Models such as Tacotron 2 and FastPitch, combined with neural vocoders like HiFi-GAN, are capable of generating natural-sounding speech that is often indistinguishable from human speech. These systems rely on digital signal processing techniques to convert raw audio into representations like Mel-spectrograms — and learned embeddings to handle text-to-audio alignment and speaker identity.

However, these deep learning models are notoriously data-hungry, requiring large amounts of high-quality, annotated speech. While English benefits from massive, well-curated datasets (e.g., LJSpeech, VCTK), low-resource languages face distinct challenges. Specifically, Lithuanian possesses a complex prosodic structure characterized by free stress and pitch accents, requiring accurate text normalization and accentuation handling. Furthermore, multi-speaker synthesis requires the model not only to learn these linguistic features but also to generalize across a latent speaker space, typically managed via d-vector or x-vector embeddings.

1.11 Research Gap

The Liepa 2 corpus, which serves as the foundation for this thesis, is a realistic scenario common for lesser-resourced languages: it contains a massive number of speakers (2621) but is highly imbalanced, with data per speaker ranging from a few seconds to over two hours.

Current literature does not adequately address how to optimally sample from such a distribution under strict computational constraints. While scaling laws [9] suggest that increasing total dataset size improves performance, training on the full 1000-hour corpus is computationally prohibitive for many academic and industrial applications. Consequently, researchers must select a subset of data (e.g., 30 hours), but it is unclear which selection strategy gives the best synthesis quality:

- Does maximizing the *speaker depth* (selecting the “Top-N” speakers with the most data) allow the model to learn stable alignments and prosody better?
- Or does maximizing the *speaker breadth* (selecting a “Balanced” or “Random” set of many speakers with less data per person) allow the model to learn a more robust, generalized representation of the language’s phonetics?

This thesis addresses this gap by evaluating different data selection strategies for training multi-speaker TTS models on the Lithuanian Liepa 2 corpus. By keeping the total training data budget fixed (30 hours) and varying the selection logic (Top-N vs. Random vs. Balanced) across autoregressive (Tacotron 2) and non-autoregressive (FastPitch) architectures, this research aims to provide practical guidelines for training high-quality TTS systems in resource-constrained, high-speaker-count scenarios.

2 Methodology

2.1 Research design

The independent variables in this study are:

- Data selection strategy: Different methods for selecting subsets of the training data.
- TTS model architecture: Comparing different TTS architectures.

The dependent variables in this study are:

- TTS model performance: Measured using objective metrics (TODO, decide) and subjective evaluations (MOS scores).

The controlled variables in this study are:

- Dataset: The Liepa 2 Lithuanian speech corpus.
- Training data size: The same total amount of training data used across all experiments.
- Training procedure: The same training hyperparameters and protocols applied across all experiments.
- Evaluation metrics: The same objective and subjective evaluation methods applied across all experiments.

2.2 Data and preprocessing

2.2.1 Liepa 2 dataset

The primary dataset for this research is the Liepa 2 corpus, a comprehensive collection of Lithuanian speech data. The corpus encompasses 1000 hours of short voice recordings from 2621 speakers, along with corresponding text transcriptions. The recordings span various speech styles and contexts, including read speech (audiobooks, news), TV and radio broadcasts, spontaneous speech.

More specifically, the dataset contains:

- Total duration: 1000 hours of speech data.
- Number of speakers: 2621 unique speakers.
- Number of utterances: 1,874,648 recorded utterances.

2.2.2 Acoustic preprocessing

The raw audio recordings from the Liepa 2 dataset are sampled at 16 kHz. To prepare the audio for TTS model training, the audio waveforms are resampled to 22,050 Hz. While resampling to a higher frequency does not add new information, it will be compatible with pre-trained vocoders that expect 22,050 Hz input.

Additional preprocessing steps, such as silence trimming and normalization, are performed by the Coqui TTS framework during training.

The acoustic processing that transforms audio waveforms into mel-spectrograms is performed on-the-fly during model training by the Coqui TTS framework. The mel-spectrogram parameters used are as follows:

TODO move to appendix

- fft_size: 1024
- win_length: 1024
- hop_length: 256
- frame_length_ms: null
- frame_shift_ms: null
- stft_pad_mode: ”reflect”
- sample_rate: 22050
- resample: false
- preemphasis: 0.98
- ref_level_db: 20
- do_sound_norm: false
- log_func: ”np.log10”
- do_trim_silence: true
- trim_db: 60
- do_rms_norm: false
- db_level: null
- power: 1.5
- griffin_lim_iters: 60
- num_mels: 80

- mel_fmin: 0.0
- mel_fmax: 8000.0
- spec_gain: 20
- do_amp_to_db_linear: true
- do_amp_to_db_mel: true
- pitch_fmax: 640.0
- pitch_fmin: 1.0
- signal_norm: true
- min_level_db: -100
- symmetric_norm: true
- max_norm: 4.0
- clip_norm: true
- stats_path: null

2.2.3 Text normalization

Before feeding text data into TTS models, the text undergoes normalization to convert it into a more consistent and model-friendly format. The Liepa 2 text already includes a significant level of normalization - for instance, the following elements are written exactly as they were spoken: dates, times, acronyms, abbreviations, numbers.

However, some additional normalization steps are applied to further standardize the text:

- Punctuation standardization: Replacing uncommon punctuation marks with more common equivalents (e.g., replacing em dashes with hyphens, and semicolons with commas).
- Removal of extraneous characters: Eliminating any remaining characters that are not letters, digits, whitespace, or basic punctuation (.,-?!).
- Whitespace normalization: Collapsing multiple consecutive whitespace characters into a single space and trimming leading/trailing whitespace.
- Accent addition: Adding accent marks (tilde, acute, grave) to words using Kirčiuoklis tool (where Kirčiuoklis suggests multiple options, accent is not added).
- Lowercasing: Converting all text to lowercase to reduce vocabulary size.
- Letter replacements: Substituting non-Lithuanian letters with their Lithuanian equivalents (‘w’ with ‘v’, ‘q’ with ‘kv’, and ‘x’ with ‘ks’).

In order to add the accents to the text, the online tool Kirčiuoklis was queried with all unique words from the dataset. The tool returned the accented versions of the words, which were then used to replace the unaccented words in the text. In cases where Kirčiuoklis provided multiple accentuation options for a word, no accent was added to avoid introducing errors.

As a result of these normalization steps, the vocabulary size is reduced from 140 characters to 41 characters, simplifying the learning task for TTS models.

2.2.4 Speaker embeddings

For multispeaker TTS training, speaker embeddings are computed using a pre-trained speaker encoder model. The speaker embedding computation process involves:

- **Speaker encoder model**: Pre-trained model from Coqui TTS based on TODO
- **Embedding extraction**: Each speaker's audio samples are processed through the speaker encoder to generate 512-dimensional speaker embeddings (d-vectors).
- **Pooling strategy**: TODO
- **Normalization**: TODO

These speaker embeddings are then used during TTS training to condition the model on speaker identity, enabling the synthesis of speech in different voices.

2.3 Data selection strategies

To investigate the impact of data selection on TTS performance, several strategies for selecting subsets of the Liepa 2 dataset were employed. All strategies maintain a fixed total training budget of 30 hours to ensure fair comparison across experiments.

2.3.1 Speaker filtering criteria

Before applying selection strategies, the dataset undergoes initial filtering:

- **Speech type filtering**: Only "read speech" samples are used, excluding spontaneous speech to ensure consistent quality and pronunciation.
- **Age group filtering**: Speakers from age groups 18–25, 26–60, and 60+ are included, excluding children (0–17) to focus on adult speech patterns.
- **Gender balancing**: Equal representation of male and female speakers when possible.

2.3.2 Selection strategies

Top-N speaker (Speaker depth): This strategy prioritizes speaker depth by selecting the N speakers with the most available data. For multispeaker training with 20 speakers, the top 10 male and top 10 female speakers (by sample count) are selected. This approach maximizes the amount of data per speaker, potentially allowing models to learn more stable speaker-specific characteristics and alignment patterns.

Balanced speaker (Speaker breadth): This strategy prioritizes speaker diversity by distributing the training budget across a larger number of speakers, with each speaker contributing roughly equal amounts of data. The selection process aims to include as many speakers as possible while maintaining the 30-hour budget constraint and gender balance.

Random sampling: As a baseline, this strategy randomly samples utterances from the filtered dataset without regard to speaker distribution. This provides a control condition to assess whether structured speaker selection provides benefits over random data selection.

2.4 Experimental design

2.4.1 Model architectures

Three TTS model architectures are evaluated in this study:

Tacotron 2 with Double Decoder Consistency (DDC): The primary autoregressive model used in this study. DDC is an enhanced version of Tacotron 2 that employs dual decoders with different reduction factors (r=1 for the main decoder, r=7 for the coarse decoder) to improve attention alignment stability. This architecture is particularly suitable for multispeaker scenarios where attention alignment can be challenging.

FastPitch: A non-autoregressive model that predicts duration and pitch explicitly, allowing for parallel generation of mel-spectrograms. FastPitch uses Transformer architecture instead of RNNs and should theoretically be less sensitive to attention alignment issues.

2.4.2 Training procedure

All models are trained using the Coqui TTS framework with consistent training procedures:

- **Training duration**: 400 epochs maximum with early stopping based on validation loss.
- **Optimization**: RAdam optimizer with learning rate scheduling using MultiStepLR (milestones at 10k, 20k, 30k, 40k steps with gamma=0.32).
- **Loss function**: Combination of decoder loss (α=0.25), post-net loss (α=0.25), SSIM losses (α=0.25), guided attention loss (α=5.0), and stop token loss (weight=15.0).
- **Batch size**: 64 for Tacotron 2 variants, 32 for FastPitch.
- **Gradient clipping**: 0.05 to prevent gradient explosion.
- **Validation**: 1% of training data held out for validation.

2.5 Model training configurations

2.5.1 Tacotron 2 with DDC hyperparameters

2 table. *Tacotron 2 DDC training configuration*

Parameter	Value
Batch size	64
Learning rate	0.001
Optimizer	RAdam
LR scheduler	MultiStepLR
Max epochs	400
Decoder reduction factor	1
DDC reduction factor	7
Attention type	Location-sensitive
Memory size	-1 (disabled)
Speaker embedding dim	512
Number of speakers	20
Stopnet	Enabled
Separate stopnet	True

2.5.2 FastPitch hyperparameters

3 table. *FastPitch training configuration*

Parameter	Value
Batch size	32
Eval batch size	16
Learning rate	0.001
Optimizer	RAdam
LR scheduler	MultiStepLR
Max epochs	400
Duration predictor layers	2
Pitch predictor layers	2
Transformer encoder layers	6
Transformer decoder layers	6
Attention heads	1
Encoder hidden dim	384
Decoder hidden dim	384

2.5.3 Vocoder configuration

For mel-spectrogram to waveform conversion, a pre-trained HiFi-GAN v2 vocoder is used across all experiments. The vocoder was pre-trained on the VCTK corpus [23] and is compatible with the

22.05 kHz sampling rate used in this study. Using the same vocoder across all experiments ensures that differences in audio quality can be attributed to the TTS model rather than the vocoder.

2.6 Evaluation methodology

2.6.1 Objective evaluation metrics

Objective evaluation is performed using standard acoustic metrics:

- **Training convergence metrics:** Training and validation loss curves, attention alignment visualization, and convergence time.

2.6.2 Subjective evaluation

Subjective evaluation is conducted through a web-based listening test application developed specifically for this study. The evaluation protocol includes:

- **Rating scale:** 5-point Mean Opinion Score (MOS) scale where 1=Very Poor, 2=Poor, 3=Fair, 4=Good, 5=Excellent.

2.6.3 Computational hardware

The experiments were conducted on a personal high-performance computing setup with the following specifications:

- CPU: AMD Epyc 7642 48-Core, 96 thread processor
- RAM: 256 GB DDR4 3200 MHz
- GPU: NVIDIA GeForce RTX 3090 with 24 GB VRAM
- Storage: 2 TB NVMe SSD

2.6.4 Implementation framework

All experiments are implemented using the Coqui TTS framework, an open-source toolkit for training TTS models. The experimental pipeline is automated using Make build system with the following components:

- **Data preprocessing:** Automated scripts for audio conversion, text normalization, and metadata generation.
- **Speaker embedding computation:** Batch processing of speaker embeddings using pre-trained encoder models.
- **Training orchestration:** Automated model training with hyperparameter configuration and checkpointing.

- **Inference pipeline:** Batch synthesis of test sentences for evaluation purposes.
- **Evaluation tools:** Integration with subjective evaluation web application and objective metric computation.

2.7 Evaluation protocol

2.7.1 Test set

Evaluation was performed on a held-out test set of 100 phrases from the Liepa 2 dataset.

2.7.2 Objective evaluation

2.7.3 Subjective evaluation

Subjective evaluation was conducted using Mean Opinion Score (MOS) tests.

3 Results and analysis

3.1 Tacotron 2 with DDC

3.1.1 Objective results

3.1.2 Subjective results

3.1.3 Qualitative analysis

3.2 FastPitch

3.2.1 Objective results

3.2.2 Subjective results

3.2.3 Qualitative analysis

4 Conclusion

4.1 Summary of findings

4.2 Contributions

4.3 Limitations of the study

4.4 Future work

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