

## OUR AMBITION

# Robust Solutions Despite Constraints.

# Developing high-performance, robust models in data-constrained environments.

Audio example: audiodynamics.dev

## VOICE / EXPRESSION



## But what if we don't have enough data?



## THE PROBLEM

# A specialized task with little to no data.

01

## The data gap.

Organizations may need robust specific solutions without having the amount of data that standard methods may require.

02

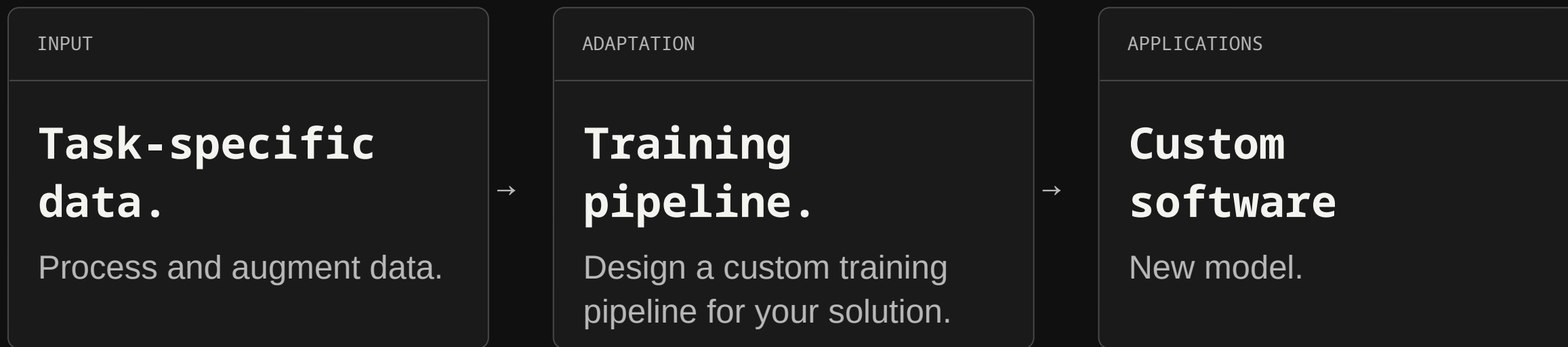
## The execution gap.

Methods that rely on massive scale may fall apart when there is little data or very limited computational resources.

**Our goal: bring intelligence to a data-constrained environment.**

## DEVELOPMENT APPROACH

**A solution that solves your problem, not  
someone else's.**



## IMPLEMENTED

## Fine-tuning pipeline + Jeju text-to-speech system

## DEMONSTRATED

## Recorded song and dialogue dubbing studies

# Why not use another solution?

## OTHER SOLUTIONS

## Cost and efficiency.

It can be inefficient to use someone else's solutions to your problem. For example, our extremism classifier targets lower-cost, task-specific inference.

## IN-HOUSE TRAINING

# Why not train ourselves?

Training in a data-constrained environment is a very particular domain. Methods such as adversarial weight perturbation need task-specific adaptation and validation.

Commercial priority: validate the strongest initial customer segment.

## TARGET CUSTOMER PROFILES

# Our target customer is

## B2B / ORGANIZATIONS

**Someone whose needs are not met.**

Perhaps their current approach is too expensive, not performant enough, or not efficient enough.

B2C / INDIVIDUALS

**Someone with little data.**

They might work in a data-constrained environment, such as health care.

Commercial priority: validate the strongest initial customer segment.

audiodynamics.dev



SCAN TO OPEN

## RECORDED PERFORMANCE STUDY

# One song. Two languages.



CHINESE → ENGLISH

00:28

# Original Chinese

00:58

# Generated English

The challenge: preserving meaning and pacing across languages.

RECORDED PERFORMANCE STUDY

# One scene. Three performances.

1 / Original Japanese performance



© AKIHAMAZI/HOUBUNSHA, ANIPLEX

JAPANESE → ENGLISH

01 **Original Japanese**

Source performance

02 **Previous English**

Earlier version

03 **New English**

Experimental audition

Here's another real world use case.

## EXTERNAL MARKET CONTEXT

**A large category.**  
**A narrow entry point.**

GLOBAL AI VOICE GENERATORS · SOFTWARE + SERVICES

2026 / ESTIMATE

**\$7.7B**

2030 / FORECAST

# \$21.8B

Category estimates, not our serviceable market or revenue forecast.

Source: Grand View Research, AI Voice Generators Market (2024–2030) · accessed 15 Sep 2026

## TARGET OPPORTUNITY

**Custom speech  
where standard  
fit is not enough.**

Specific languages.  
Specialized workflows.  
Limited task-specific audio.

## SELECTED ALTERNATIVES

**Audio is a crowded field, but we believe our solutions are robust.**

| ALTERNATIVE                   | Documented capability.                                          | Goals to validate.              |
|-------------------------------|-----------------------------------------------------------------|---------------------------------|
| <b>ElevenLabs</b>             | Multilingual dubbing; speaker identity and emotional tone.      | Live and on-device performance. |
| <b>Microsoft Azure Speech</b> | Custom speech recognition and custom synthetic voices.          | Highly expressive audio.        |
| <b>OpenVoice</b>              | Short-reference voice cloning and cross-language style control. | Control and performance.        |

## Our test to win: less task-specific data at matched quality.

Sources below; vendor-reported capabilities, not head-to-head results.

ElevenLabs

## Microsoft: recognition

Microsoft: voice

OpenVoice

Reviewed 15 Sep 2026

MOAT THESIS

# From custom models to cumulative know-how.

---

BUILT

## Adaptation capability

Fine-tuning pipeline  
and Jeju text-to-speech  
development.

---

TO VALIDATE

## Training-data efficiency

Fewer task-specific  
recordings at the same  
quality level.

---

POTENTIAL TO COMPOUND

## Reusable methods

Carry useful adaptation  
methods into the next  
language or workflow.

# Custom scope. Recurring access.

## B2B / CUSTOM PROJECTS

# Project revenue

Pricing reflects the language,  
workflow and scope of the  
custom speech solution.

## B2C / SUBSCRIPTION + USAGE

## Recurring access

Subscriptions and pay-as-you-go fees give consumers access to speech tools.

Next commercial proof: a priority buyer, willingness to pay and delivery economics.



We are also quite experienced with natural language processing.

# Let's attempt to create a language model from scratch.

## LibreLM

TRAINING BRIEF / SEPTEMBER 2026

### Compact models. Measured training.

Two later pretraining runs, with GPT-2 Small as the parameter-count reference.

**78%**

fewer total parameters than GPT-2 Small  
27.57M vs. 124.44M · size comparison

**1h 58m**

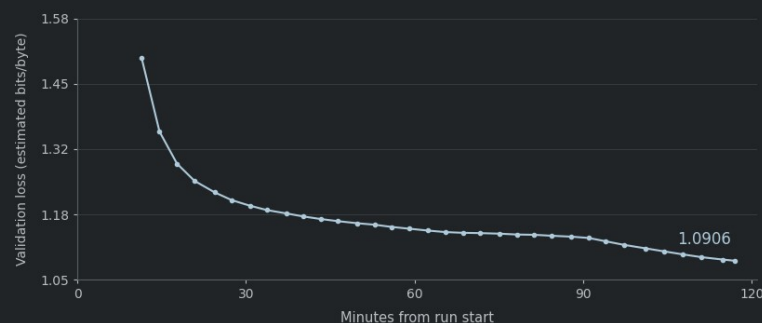
27.57M selected run: start to completion  
551M nominal positions · 78.1k positions/s

**0.9361**

109.04M run: final validation loss  
Pretraining · estimated bits/byte

#### The compact run

27.57M parameters · compact tokenizer · 34 validation points



#### Embedding and non-embedding parameters

Millions of parameters; tied vocabulary weights counted once.

| Model           | Embedding | Non-emb. | Total  |
|-----------------|-----------|----------|--------|
| LibreLM 27.57M  | 6.29      | 21.28    | 27.57  |
| LibreLM 109.04M | 12.58     | 96.46    | 109.04 |
| GPT-2 Small     | 39.38     | 85.06    | 124.44 |

#### Recorded elapsed time

27.57M model

**1h 58m**

Start to completion

109.04M model

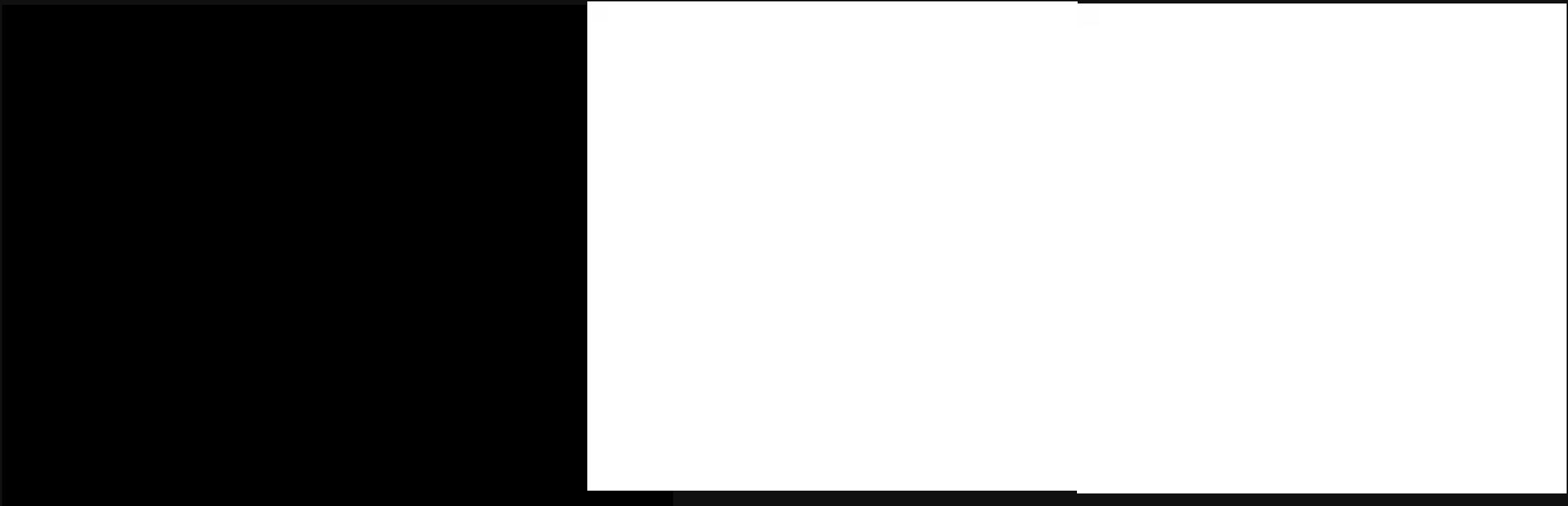
**61h 19m**

Includes gaps and interruptions

Since I did, this mostly just for fun and trained on my laptop 100 million parameter, 60 hour estimate is wrong. I actually paused the training run several times so I could play video games or do other stuff.

## What about computer vision?

**Let's do something no one's done before.**



There are two models. First is an image decomposition model which decomposes existing images into valid Photoshop sequences. The second takes textual prompt and creates novel sequences to create a novel image.

# Research depth. Hands-on execution.

## CO-FOUNDER

# Built a hybrid Mamba–Transformer masked-diffusion model in PyTorch.

Built and sold software; supported users and incorporated product feedback.

# Boeing internship, summer 2024: business case development and technical proposals.

CO-FOUNDER / UCLA COMPUTER SCIENCE

Worked with Georgetown professors on  
agentic ML for high-dimensional biomedical data.

Experience building and evaluating language-model and retrieval systems.

Python-based machine-learning pipelines  
and rigorous model-performance testing.

## PROPOSED PROOF POINTS

**Make it work.  
Then make it repeatable.**

01

# Measure

Compare data required at matched quality against named baselines.

02

# Validate

Test a specific buyer's workflow, budget and acceptance criteria.

03

# Repeat

Reuse what works; measure  
delivery cost and  
repeat demand.

## Quality evidence first. Commercial evidence next.

You can view a folder of our audio examples [here](#).

OSKAR JONIENTZ / CO-FOUNDER

oskarjonientz@gmail.com



SCAN TO OPEN