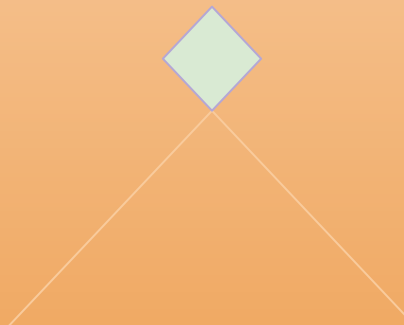


Speech technology

Trends, limitations & future

Vivian van Oijen



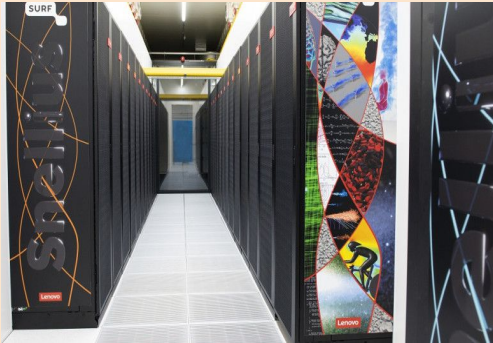
Hello!

Hello!



Machine learning
@SURF

Hello!



SURF COMMUNITIES

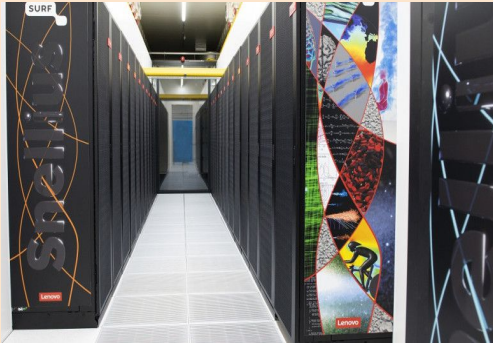
Deel je expertise met de SURF-community

AI in Education

Machine learning
@SURF



Hello!



Machine learning
@SURF



Speech technology

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For learners

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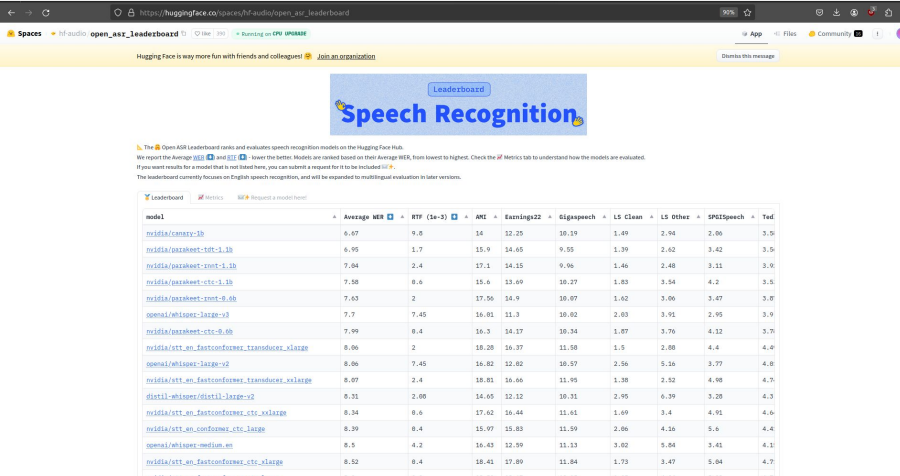
For parents

On-demand help makes homework time a breeze.

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State of the Art

State of the Art Hugging Face Leaderboard



Speech Recognition

Open ASR Leaderboard cards and evaluate speech recognition models on the Hugging Face Hub. We report the Average WER and RTF. Lower is better. Models are ranked based on their Average WER, from lowest to highest. Check the JF Metrics tab to understand how the models are evaluated. If you want results for a model that is not listed here, you can submit a request for it to be included in it.

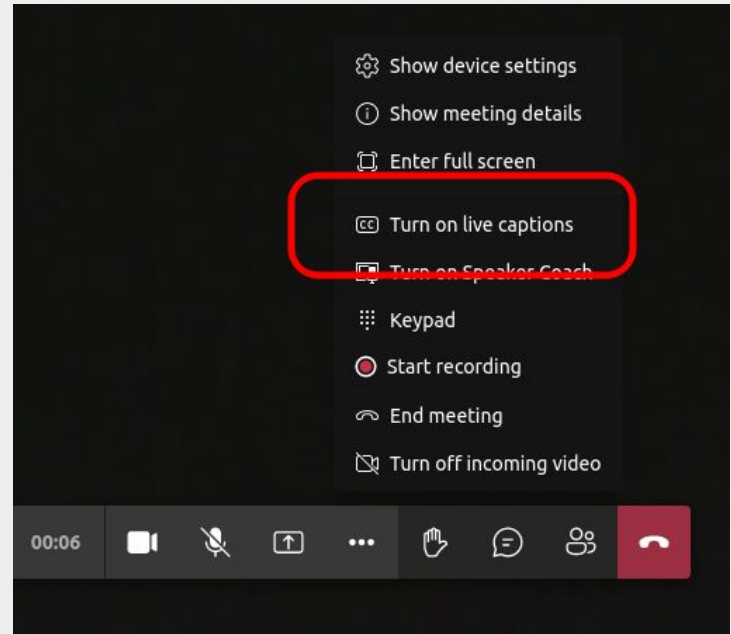
The leaderboard currently focuses on English speech recognizers, and will be expanded to multilingual evaluation in later versions.

model	Average WER	RTF (s-1)	BLEU	ASR	Examing22	Gigaspeech	LS Clean	LS Other	SPEECSpeech	Ted
rytdia/cmory-1b	6.67	9.6	14	12.25	16.19	1.49	2.94	2.06	3.5	
rytdia/parabeet-tst-1.1b	6.95	1.7	15.9	14.65	9.55	1.39	2.62	3.42	3.5	
rytdia/parabeet-tst-1.1b	7.04	2.4	17.1	14.55	9.96	1.46	2.48	3.11	3.9	
rytdia/parabeet-ctc-1.1b	7.56	6.6	15.6	13.60	10.27	1.83	3.54	4.2	3.5	
rytdia/parabeet-tst-9.1b	7.63	2	17.56	14.9	10.07	1.62	3.06	3.47	3.8	
openai/whisper-large-v3	7.7	7.45	16.81	11.3	10.02	2.83	3.91	2.95	3.9	
rytdia/parabeet-ctc-9.1b	7.99	6.4	16.3	14.17	10.34	1.87	3.76	4.12	3.7	
rytdia/tst_en_fastconformer_transducer_xlarge	8.06	2	18.28	16.37	11.58	1.5	2.88	4.4	4.4	
openai/whisper-large-v2	8.06	7.45	16.82	12.82	10.57	2.56	3.16	3.77	4.8	
rytdia/tst_en_fastconformer_transducer_xlarge	8.07	2.4	18.81	16.66	11.95	1.38	2.82	4.08	4.7	
distil-whisper/distil-large-v2	8.31	2.00	14.65	12.12	10.31	2.95	4.39	3.28	4.3	
rytdia/tst_en_fastconformer_ctc_xlarge	8.34	6.6	17.62	16.44	11.61	1.49	3.4	4.91	4.6	
rytdia/tst_en_fastconformer_ctc_large	8.39	6.4	15.97	15.83	11.59	2.06	4.16	5.6	4.4	
openai/whisper-medium-v3	8.5	4.2	16.43	12.99	11.13	1.92	3.84	3.41	4.1	
rytdia/tst_en_fastconformer_ctc_xlarge	8.52	6.4	18.41	17.89	11.84	1.73	3.47	5.04	4.7	
rytdia/tst_en_fastconformer_ctc_large	8.9	6.2	18.59	18.67	12.15	1.95	4.04	5.83	4.7	

https://huggingface.co/spaces/hf-audio/open_asr_leaderboard

State of the Art

Study case 1: Teams



State of the Art

Study case 2: Canary & Parakeet



Generative AI

NVIDIA NeMo

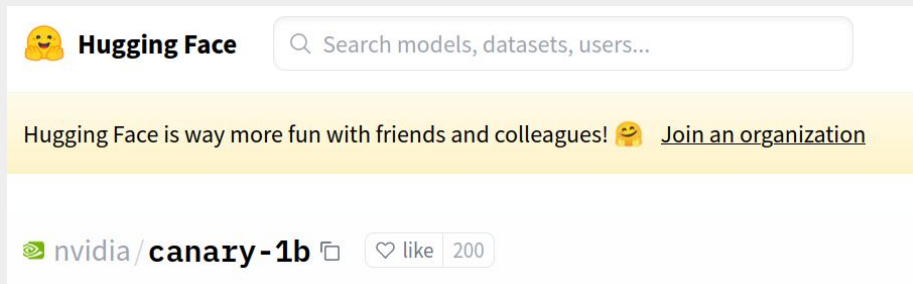
Build, customize, and deploy generative AI.

[Get Started](#)

[Video](#) | [Solution Brief](#) | [For Developers](#)

State of the Art

Study case 2: Canary & Parakeet

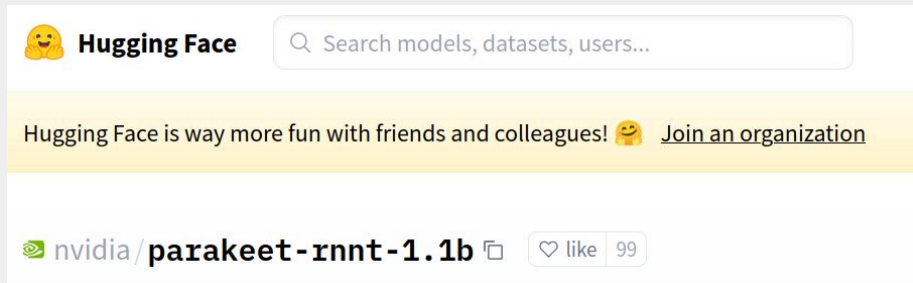


Hugging Face

Search models, datasets, users...

Hugging Face is way more fun with friends and colleagues! 😊 [Join an organization](#)

nvidia/**canary-1b** 📄 like 200



Hugging Face

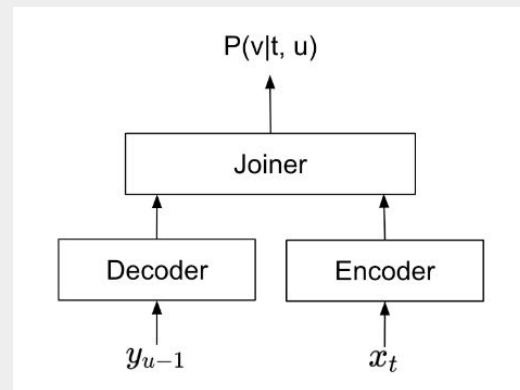
Search models, datasets, users...

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nvidia/**parakeet-rnnt-1.1b** 📄 like 99

State of the Art

Study case 2: Canary & Parakeet



How to use Parakeet-TDT

To run speech recognition with Parakeet-TDT, you'll need to install [NVIDIA NeMo](#). It can be installed as a pip package, as shown below. Cython and PyTorch (2.0 and above) should be installed before trying to install NeMo.

```
pip install nemo_toolkit['asr']
```

Once NeMo is installed, you can use Parakeet-TDT to recognize your audio files as follows:

```
import nemo.collections.asr as nemo_asr
asr_model = nemo_asr.models.ASRModel.from_pretrained(model_name="nvidia/parakeet-tdt-1.1b")
transcript = asr_model.transcribe(["some_audio_file.wav"])
```

State of the Art

Study case 3: Whisper



Paper

Robust Speech Recognition via Large-Scale Weak Supervision

Alec Radford^{*1} Jong Wook Kim^{*1} Tao Xu¹ Greg Brockman¹ Christine McLeavey¹ Ilya Sutskever¹

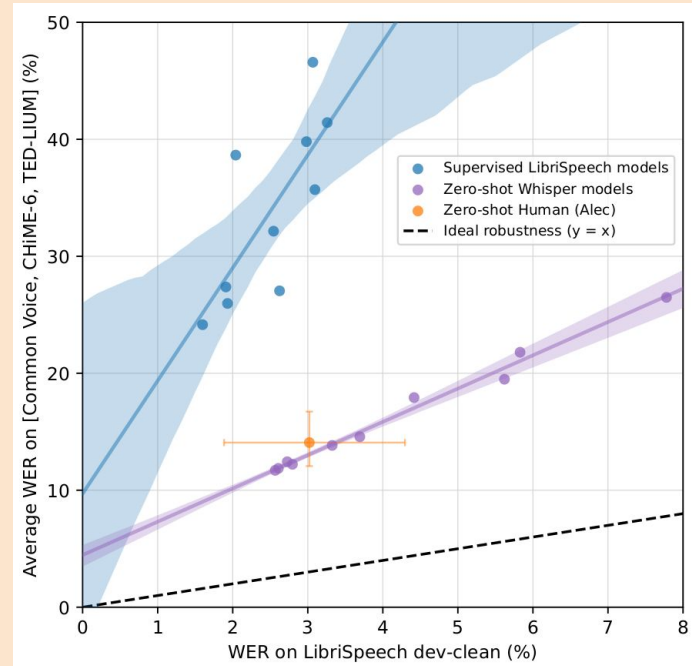
Abstract

We study the capabilities of speech processing systems trained simply to predict large amounts of transcripts of audio on the internet. When scaled to 680,000 hours of multilingual and multitask supervision, the resulting models generalize well to standard benchmarks and are often competitive with prior fully supervised results but in a zero-shot transfer setting without the need for any fine-tuning. When compared to humans, the models approach their accuracy and robustness. We are releasing models and inference code to serve as a foundation for further work on robust speech processing.

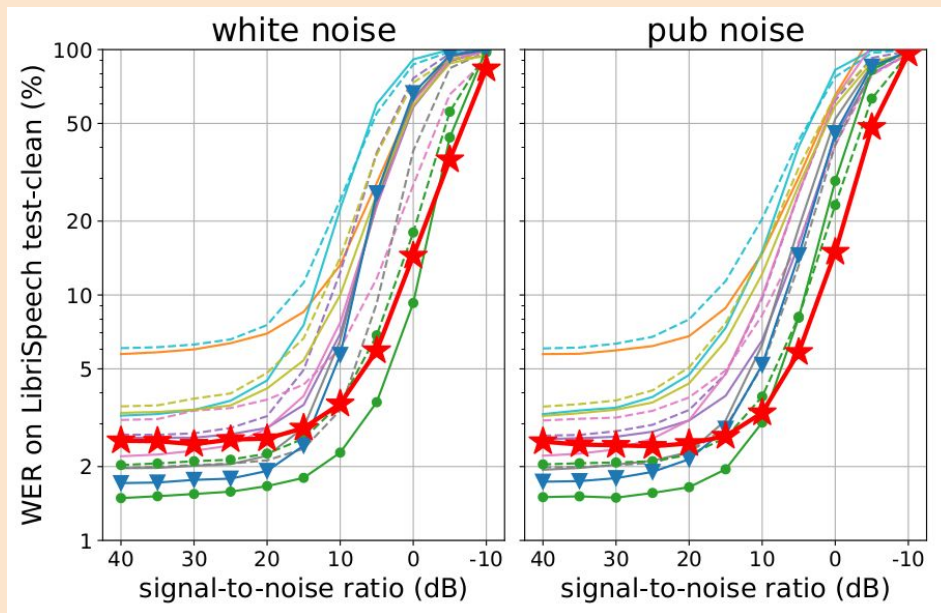
methods are exceedingly adept at finding patterns within a training dataset which boost performance on held-out data from the same dataset. However, some of these patterns are brittle and spurious and don't generalize to other datasets and distributions. In a particularly disturbing example, Radford et al. (2021) documented a 9.2% increase in object classification accuracy when fine-tuning a computer vision model on the ImageNet dataset (Russakovsky et al., 2015) without observing any improvement in average accuracy when classifying the same objects on seven other natural image datasets. A model that achieves "superhuman" performance when trained on a dataset can still make many basic errors when evaluated on another, possibly precisely because it is exploiting those dataset-specific quirks that humans are oblivious to (Geirhos et al., 2020).

<https://arxiv.org/abs/2212.04356>

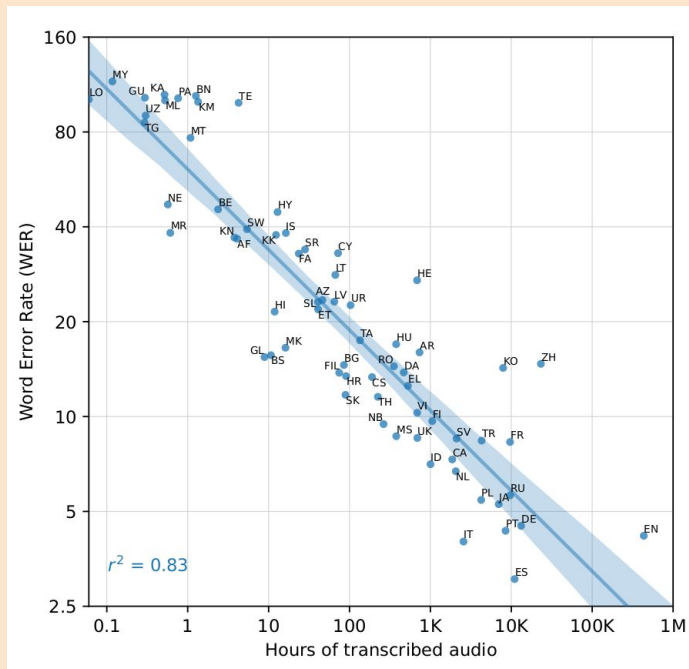
Paper



Paper



Paper



Paper

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<https://arxiv.org/abs/2212.04356>

"Demo"

WhisperX template

Step 1: Change kernel
Make sure in the top-right of this window the selected kernel is 'whisperX (C:\python311\python.exe)'. If you see 'Python 3 (C:\python311\python.exe)', just click on it to change it to the whisperX kernel.

Step 2: Create input and output folders
It is recommended to store audio files in a 'your' folder on a storage volume. The storage volume can be found from your home folder in the folder: ~\B06A. The storage volume will have the same that you have assigned to it when creating the storage volume.

- Navigate to the storage volume in the panel on the left.
- Create a new folder called 'my_voice' (or 'my_voice') by clicking on the 'New' button (Folder with plus sign) in the panel on the left.
- Open (choose a different folder name, remember to change the filename in the code cell) below
- Create a folder called 'input'.
- Create another folder called 'output'.

Step 3: Upload audio

- To upload an audio file, navigate to 'B06A: Folder (previous step)'
- Press the 'Upload Files' button (green arrow) in the panel on the left to upload the file.

Step 4: Run the code cell below to import whisperX and define required variables

```
import whisper
import whisperX
import os

DEVICE = "cuda"
batch_size = 24 # reduce if you are OOM
compute_type = "float32" # change to "float16" if you are OOM and don't reduce accuracy
whisperX_model = "large-v3" # options: "small", "medium", "large-v2"
url_loader = True # True: Use url_loader, False: Use local_loader
highlight_url_loader = True
```

```
Transcribe audio

1 from openai import OpenAI
2 client = OpenAI()
3
4 audio_file= open("/path/to/file/audio.mp3", "rb")
5 transcription = client.audio.transcriptions.create(
6     model="whisper-1",
7     file=audio_file
8 )
9 print(transcription.text)
```

WillMa

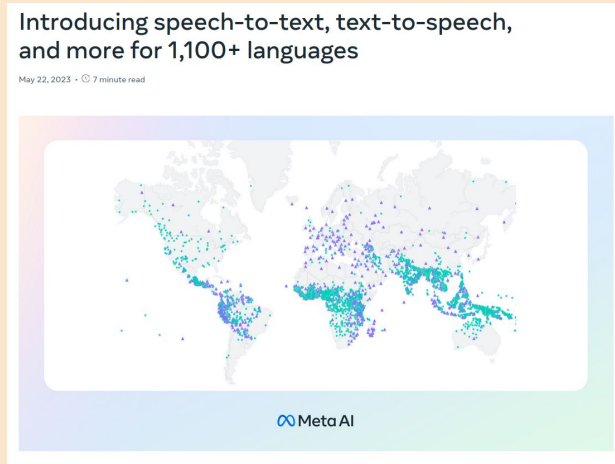
Whisper speech-to-text Dutch ☆

Loaded: X

Currently only implemented for API access.

START CHAT →

The other way around: text to speech!



Deepgram



Nova

Unmatched performance and value

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Whisper

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Custom trained speech models give accuracy a noticeable boost, especially on unique customer jargon. High throughput models are also available to meet enterprise scalability requirements.



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Some commercial alternatives...

Limitations

Limitations

Services

Open models

Limitations

Services

- Little transparency
- Requires sharing your data

Open models

Limitations

Services

- Little transparency
- Requires sharing your data

Open models

- Sometimes less quality
- Less user friendly

Limitations

View on GitHub



Dutch Open Speech Recognition Benchmark

Results of Dutch ASR models, collected by the community

https://opensource-spraakherkenning-nl.github.io/ASR_NL_results/

Future

Future

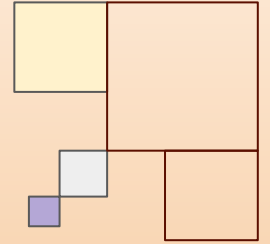
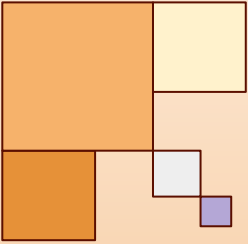
How do we overcome current limitations

1. Quality

We need data

2. Infrastructure

Trusted party that provides API and UI



Thank you!

Vivian van Oijen

