
ATCO2 corpus

A Large-Scale Dataset for Research on Automatic Speech Recognition and Natural Language Understanding of Air Traffic Control Communications

Juan Zuluaga-Gomez^{*,1,2} Karel Vesely³ Igor Szöke^{3,4} Petr Motlicek^{1,3}
Martin Kocour³ Mickael Rigault⁵ Khalid Choukri⁵ Amrutha Prasad^{1,3}
Saeed Sarfjoo¹ Iuliia Nigmatulina¹ Claudia Cevenini⁶

Pavel Kolčárek⁷ Allan Tart⁸ Jan Černocký³

¹Idiap Research Institute, Martigny, Switzerland

²Ecole Polytechnique Federale de Lausanne (EPFL), Lausanne, Switzerland

³Brno University of Technology, Speech@FIT, IT4I CoE, Brno, Czech Republic

⁴ReplayWell, Brno, Czech Republic

⁵Evaluations and Language Resources Distribution Agency (ELDA), Paris, France

⁶Romagna Tech, Forli, Italy

⁷Honeywell, Brno, Czech Republic

⁸OpenSky Network, Burgdorf, Switzerland

*Corresponding author: juan-pablo.zuluaga@idiap.ch

Abstract

Abstract: Personal assistants, automatic speech recognizers and dialogue understanding systems are becoming more critical in our interconnected digital world. A clear example is air traffic control (ATC) communications. ATC aims at guiding aircraft and controlling the airspace in a safe and optimal manner. These voice-based dialogues are carried between an air traffic controller (ATCO) and pilots via very-high frequency radio channels. In order to incorporate these novel technologies into ATC, large-scale annotated datasets are required to develop the data-driven AI systems. **Two examples are automatic speech recognition (ASR) and natural language understanding (NLU).** However, ATC is considered a low-resource domain. In this paper, we make several contributions aiming at overcoming these disadvantages. First, we introduce the *ATCO2 corpus*, a dataset that aims at fostering research on the challenging ATC field, which has lagged behind due to lack of annotated data. Second, we open-source a GitHub repository¹ that contains data preparation and training scripts useful to replicate some of our baselines related to ASR and NLU for ATC communications. The *ATCO2 corpus* covers 1) data collection and pre-processing, 2) pseudo-annotations of speech data, and 3) extraction of ATC-related named entities. The *ATCO2 corpus* is split into three subsets. 1) *ATCO2-test-set corpus* contains 4 hours of ATC speech with manual transcripts and a subset with gold annotations for named-entity recognition (callsign, command, value). 2) The *ATCO2-PL-set corpus* consists of 5281 hours of unlabeled ATC data enriched with automatic transcripts from an in-domain speech recognizer, contextual information (list of relevant n-gram sequences per utterance), speaker turn information, signal-to-noise ratio estimate and English language detection score per sample. These two are available for purchase through ELDA in <http://catalog.elra.info/>

¹Our code will be stored in the following public GitHub repository <https://github.com/idiap/atco2-corpus>.

25 en-us/repository/browse/ELRA-S0484/. 3) The *ATCO2-test-set-1h corpus*
26 is a one-hour subset from the original test set corpus, that we are offering for free in
27 the following website: <https://www.atco2.org/data>. We expect the *ATCO2*
28 *corpus* will foster research on robust ASR and NLU not only in the field of ATC
29 communications but also in the general research community.

30 **Keywords:** Air Traffic Control Communications, Natural Language Processing, Automatic Speech
31 Recognition, Spoken Language Understanding, Signal Processing

32 1 Introduction

33 The corpus introduced in this research is within the domain of civil air traffic control (ATC) com-
34 munications and management. ATC aims at managing the airspace in a safe and optimal manner.
35 The communication is either via spoken or data-link messages, while the time-critical messages are
36 always spoken. These communications involve an air traffic controller (from now on, ATCO) issuing
37 spoken flight instructions to aircraft pilots during all phases of the flight. The dialogue follows a
38 well-defined grammar and set of rules that ensures safety, reliability, and efficiency [1, 2]. This can
39 be seen as a multi-speaker and multi-turn conversation.

40 Commonly, an ATCO addresses several pilots in a short period of time, which in turns becomes the
41 main cause of increased workload and limiting factor to increase the overall system capacity, i.e., there
42 is large space for optimization by only reducing ATCO’s workload. **A significant bottleneck in the**
43 **pipeline is the considerable latency arising from an ATCO issuing a command by voice and inserting**
44 **it manually into the ATCO’s workstation (for control and record).** Recent advances in automatic
45 speech recognition (ASR) and natural language processing (NLP) technologies have opened new
46 ways where ATCO’s workload can be reduced² by integrating different systems in a cascade fashion.
47 The systems for extracting the actual meaning from the original audio signal are commonly known as
48 spoken language understanding (SLU).

49 Our previous works have made sizeable progress on independent systems for ATC, such as, robust
50 ASR [3], NLP [4], and diarization and segmentation [2]. However, until today, these systems are
51 close to non-existent in real-life ATC operations. In part, this is due to the intrinsic complexity of the
52 task, and mainly to the lack of annotated data available to train these data-driven systems [5].

53 This paper introduces the *ATCO2 Corpus* derived from a joint contribution from Clean Sky 2 Joint
54 Undertaking (JU) and EU-H2020. ATCO2³ project developed a platform to collect, organize, pre-
55 process and automatically annotate ATC dialogues⁴. The main bottleneck towards ASR or natural
56 language understanding (NLU) techniques for ATC are the lack of annotated data. Further, its
57 collection and annotation requires trained personal, thus, the whole pipeline becomes excessively
58 costly and impractical. This study presents how the entire data collection and annotation process can
59 be efficiently accelerated by using already existing machine learning (ML) concepts.

60 The overall *ATCO2 Corpus* ecosystem is depicted in Figure 1. We release two corpora targeted to
61 ATC for research in robust ASR, NLP and NLU, i.e., the i) *ATCO2-test-set corpus* and ii) *ATCO2*
62 *pseudo-labeled set corpus* (*ATCO2-PL-set corpus*). The former contains word-level and named
63 entities⁵ gold annotations. In total, we release 4 hours of speech with various useful metadata (see the
64 blue circles from Figure 1). The latter, *ATCO2-PL-set corpus*, contains ~5281 hours of ATC audio
65 recordings, where each utterance includes a detailed set of metadata. For instance: pseudo-transcripts
66 obtained from an in-domain ATC ASR system (the pseudo transcripts contain also diarization and
67 segmentation information), contextual information (list of word sequences for lattice-boosting of
68 callsigns), signal-to-noise ratio (SNR) estimate, and English language detection (ELD) scores (see the
69 green circles from Figure 1). Even though this is not the first publicly available corpus related to ATC

²In fact, workload reduction is also translated in reduced flight time, which decreases overall operational costs and the environmental impact of aircraft.

³AuTomatic COllection and processing of voice data from Air-Traffic COmmunications, website: <https://www.atco2.org/>.

⁴We believe this pipeline can be easily adapted to other applications, where data scarcity is a latent problem, but access to unlabeled/non-annotated data is permissible e.g., patient–physician dialogues.

⁵Our Named Entity Recognition (NER) classes are: Callsign, Command, Value and Unnamed Phrase. The NER labels can be used to train/test an SLU system for slot filling.

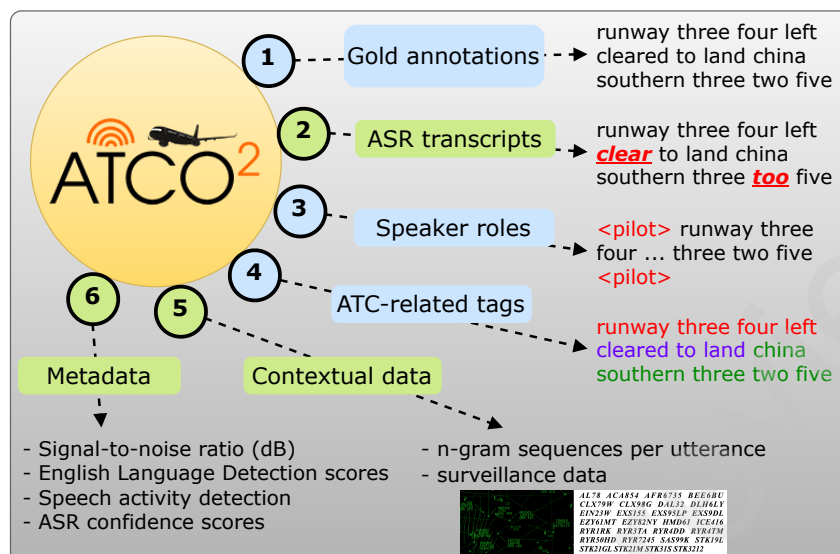


Figure 1: *ATCO2 corpus ecosystem*. Blue circles denote annotations only available for *ATCO2 test set corpus*. Green circles denote annotations and metadata available for both *ATCO2 test set* and *ATCO2 pseudo-labeled corpus sets* (see Table 1 bottom).

communications [6, 7, 8, 9], to author’s knowledge, this is the first corpus that conveys annotated data for text and spoken-based tasks e.g., named entity recognition (NER), slot filling (SF), or sequence classification.

An overview of the data processing pipeline developed by ATCO2 and used to collect the *ATCO2 corpus* is depicted in Figure 2 (a more detailed description is in Section 4.3). The data processing pipeline consists of 1) speech pre-processing tools (segmentation, volume adjustment and discarding noisy recordings), 2) diarization (split audio per speaker), 3) ASR, 4) English language detection (ELD), 5) speaker role detection (SRD) e.g., ATCO or pilot, and 6) labeling of callsigns, commands and values with named entity recognition (NER). We used this pipeline to produce the *ATCO2-PL-set corpus* and *ATCO2-test-set corpus*, which cover more than ten airports worldwide. The *ATCO2 corpus* is publicly available in ELDA catalog at the following URL: <http://catalog.elra.info/en-us/repository/browse/ELRA-S0484/>. Further details about the data collection and pre-processing is covered in the Appendix B and our previous paper [2].

We also emphasize that the developed pipeline was not only used to collect the data presented in this paper, but also is running live at <https://www.spokendata.com/atco2>. The data is automatically fed, filtered, and pre-transcribed, so the amount of data will increase. We are searching for volunteers, both for feeding data from new airports (see Section 4.1) or for correcting the automatic transcripts (see Sections 4.2). In general, the *ATCO2 corpus* can be used to produce a robust ASR system for the ATC domain, and with its NER annotations it is possible to train models for SLU applications for extracting meaning from speech (e.g., callsign or command detection). However, we also believe that the pipeline developed by ATCO2 can be also adapted to data collection and annotation of different domains, e.g., call-centers conversations, or medical recordings.

Motivation: speech and text-based processing tools for ATC data could work better if we had a large amount of reliably annotated data. However, the collection and manual annotation requires qualified personnel, and it is costly. In addition, the recordings are often noisy (SNR below 15 dB), accented or with high speech rate (compared to conversational, read or spontaneous speech). Aligned to solve this, *ATCO2 corpus* answers four big challenges:

Current ATC corpora are limited to automatic speech recognition. However, ASR is only a small submodule of the whole pipeline and many more downstream tasks are indeed required, e.g., ATC-related NER or callsign detection and extraction. In our case, those are callsigns, commands and their values. *ATCO2 corpora* goes in this line and further by releasing gold annotations to train systems on ASR, NER, ELD, and SRD.

upon the *ATCO2 corpora* presented in this paper. Additionally, we hope that the presented baselines will foster research in the fields of ASR and NLP for ATC communications.

The paper is organized as follows. Section 2 covers previous work on ASR and NLP directed to ATC communications. Section 3 explains our proposed methodologies for the standardization of ATC communications annotation process. The data collection protocol, pre- and post-processing steps undertaken during the annotation process of *ATCO2 corpora* are described in Section 4. *ATCO2 corpora* data statistics are reviewed in Section 5. Section 6 and 7 convey the proposed baselines on ASR and NLP, respectively. Section 8 covers the main legal and ethical implications of ATC data collection. Finally, we conclude this paper in Section 9 with final remarks and prospect of future work.

2 Previous Work on ATC Corpora

Currently, there is a huge diversity of databases related to speech and text tasks that have been promoting advances in artificial intelligence (AI). However, ATC communications are still considered an under resourced and underexplored area [16, 17]. Despite the growing interest in text and speech technologies for ATC, there is not a commercial ASR engine due to: (i) **deficiency in terms of required performance (under 5% WER [18])**, and (ii) **lack of large-scale annotated speech data. The costly data collection and annotation makes it impractical, when transfer to a new airport requires data collection and annotation.**

2.1 Background

Research seeking to aid ATCOs by ASR date as back as late 70s'. [19] proposed a system for isolated word recognition, speaker verification and commands recognition for military applications. Exploratory research towards integration of ASR technologies to aid ATCOs started in the late 80s with Hamel et al. [20]. Several other research directions cover user-friendly and robust automatic systems to train ATCOs, or the so called 'pseudo-pilots' [21]. Akin training systems have been proposed in [21, 22, 10]. We shortlist the three biggest European-based projects that aim at developing speech and text-based tools to aid ATCOs in their daily tasks. Initially, MALORCA⁸ project was a step forward in demonstrating that ASR tools can cut down ATCOs workload [23] while increasing the overall efficiency [24]. Then, HAAWAI⁹ project has led initiatives to extract key entities (e.g., NER or SF) in the transcribed dialogues produced by an ASR system [25]. Finally, ATCO2 project (our corpora) aimed at reducing the human work needed to develop ASR and SLU tools for ATC, mainly by integrating semi-supervised techniques in these systems [2, 4]. While the MALORCA and HAAWAI corpora are not public, in ATCO2 we developed a pipeline to collect large quantities of ATC speech data, which are distributed to the public through ELDA.

2.2 Command-related ATC Corpora vs Standard Corpora

The ATC speech corpora differ vastly from the standard ASR-training corpora. The root of the discrepancy is not only in grammar and vocabulary, but also in the audio quality. The standard corpora like Librispeech [13], Common Voice [11], AMI [26] or TED-LIUM [27] either target conversational, read or spontaneous speech while also being mostly regarded as 'clean speech'. On the other hand, ATC corpora comprises considerably higher noise levels e.g., normally below 15dB signal-to-noise (SNR) ratio, heavily accented, high speech rate and artifacts. Previous work has demonstrated that the use of standard corpora do not bring significant improvement in ASR for ATC [4].

Even though, ATC English corpora share common grammar, there is still a domain shift caused by non-native speakers. One example are ATCOs from Switzerland. Even though they are from the same country, accent varies depending on the location. This, in turn, increases the challenge of developing robust enough systems that generalize well across different in-domain environments. Therefore, a

⁸MAchine Learning Of speech Recognition models for Controller Assistance, website: <http://www.malorca-project.de/wp/>.

⁹Highly Automated Air traffic controller Workstations with Artificial Intelligence Integration, website: <https://www.haawaii.de/wp/>.

Table 1: Air traffic control communications related databases. This table list public and private ATC databases. The *ATCO2 corpora* are public databases. [†]full database after silence removal. ^{††}speaker accents depend on the airport’s location, however, the accent of pilots are not known at any time of the communication due to privacy regulations.

Database	Details	Licensed	Accents	Hours [†]	Ref
<i>Private databases</i>					
HAAWAII	Real data from Iceland and London airports	✗	Icelandic, British	47	[16]
MALORCA	Real data from Vienna and Prague airports	✗	German, Czech	13	[28, 29]
AIRBUS	Real data from Toulouse-Blagnac airport	✗	French	100	[30]
VOCALISE	Real data from terminal maneuvering area and area control center in France	✗	French	150	[31]
ENAC	Real data from two French en-route control centers and one major airport	✗	French	22	[32]
<i>Public databases</i>					
ATCOSIM	Simulated in studio, added cockpit noise. Recordings split by gender (Male/Female)	✓	Swiss German, German, French	10.7	[7]
UWB-ATCC	Real data from Prague airport	✓	Czech	13.2	[8]
LDC-ATCC	Real data from 3 US airports: Logan International, Washington National and Dallas Fort Worth airports	✓	American English	26.2	[9]
HIWIRE	Simulated in studio, ATC prompts, added cockpit noise	✓	French, Greek, Italian, Spanish	28.7	[33]
<i>Released corpora by ATCO2 project</i>					
<i>ATCO2 corpora</i>	Data from different airports and countries		Several ^{††}		
↔ <i>ATCO2-test-set</i>	Real data for ASR and NLP research.	✓	↔	4	
↔ <i>ATCO2-PL-set</i>	Pseudo-labeled real data for research in ASR and NLU.	✓	↔	5381	[2]
<i>Free access databases released by ATCO2 project</i>					
↔ <i>ATCO2-test-set-1h</i>	'ASR dataset': public 1 hour sample, subset of <i>ATCO2-test-set-4h</i> . https://www.atco2.org/data	✓	↔	1	[2]
↔ <i>ATCO2-ELD set</i>	'LID dataset': public dataset for English language detection. https://www.atco2.org/data	✓	↔	26.5	[34]

non-adapted ASR or NLP system will provide significantly worse performance due to unseen accents, out-of-vocabulary (OOV) words or simply due to discrepancy in the recording procedure.

Further details about the corpora produced by previous projects related to ATC communications are covered in Table 1. Current ATC corpora can be classified into two, public and private databases. Public databases normally require a small fee and sometimes are restricted to only-research purposes. While private corpora¹⁰ are only usable along the concerned project, for instance, to train and test their ATC-related systems. One example is MALORCA, where the two produced corpora, *Prague* and *Vienna* datasets, are widely used by partners from HAAWAII and ATCO2 projects.

3 How To Transcribe Air Traffic Control Audio Data?

This section reviews our collective efforts to provide an unambiguous and clear protocol on how to annotate ATC speech data. We aim at avoiding as much as possible the errors caused by OOV words and phonetic dissimilarities (e.g., “hold in position” and “holding position”, or, “climb to two thousand” and “climb two two thousand”). We also rely on the International Civil Aviation Organization (ICAO), which defines a standard phraseology [1] to reduce these errors during the communications.¹¹ This section first formulates an approach to unify transcripts from different public ATC databases (see Table 1 and Appendix C). Second, it discusses how to craft a lexicon tailored to ATC communications.

¹⁰In fact, nearly all ongoing and former projects in the area of ATC prohibit the release of databases, code, and AI models due to privacy issues.

¹¹Previous work in [35] proposes a novel ontology agreed by several European institutions to annotate unambiguously these dialogues.

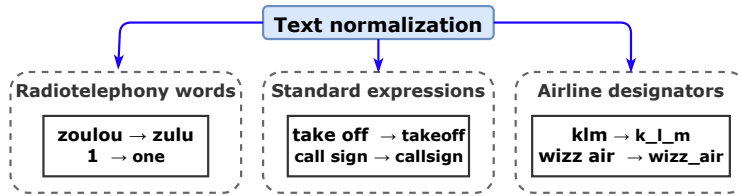


Figure 3: Text normalization applied to the transcription process of ATCO2 corpora. Further examples in Appendix C.

3.1 Unification of Transcripts

Differently from other corpora, ATC is regulated by a set of rules and a defined grammar. We have seen that in the already available databases (see Table 1), the transcription process and annotation rules widely diverge. There is not a clear path to follow when it comes to data collection and annotation. Even for a single database, it can be challenging to specify and follow their transcription conventions. One example are numbers. In ATC communications, numbers are key for addressing the aircraft or obtaining its speed or altitude. Several databases have opted to annotate numbers as digits (e.g., $1 \rightarrow 1$), while other databases have chosen to use words (e.g., $1 \rightarrow one$). That is why the ATCO2 corpus also aims at providing a set of good practices and rules to correctly and unambiguously annotate ATC dialogues¹². Therefore, if we succeed in reducing the variability of “writing the same thing in many ways”, we can considerably reduce the errors committed by subsequent systems in the pipeline, e.g., ASR or NLU. The next logic step, before starting the annotation process, is to define a set of rules to either, unify the transcripts of already available corpora¹³ or, to annotate a new corpus.

In general, we apply three different text normalization approaches (see Figure 3) to foster good practices on the ATC-transcription process. We redirect the reader to Appendix C, where additional mapping rules are covered in Table 8. These mapping rules are applied as text filters. We use them to reformat the human-created gold transcripts for the ASR and NLP systems. For the annotation of *ATCO2-test-set corpus*, we also defined an annotation manual that is reachable from the transcription platform <https://www.spokendata.com/atco2>.

3.2 Lexicon

The lexicon is a table that maps words into pronunciations (phoneme-strings). It is a resource used by the HMM-based ASR tools. Our lexicon is based on the CMU Pronouncing Dictionary¹⁴, which defines the phoneme set, and which is used as the training data for the grapheme-to-phoneme (G2P) module that synthesizes pronunciations of “new words”. We gather all possible words from the training corpora, and we add some other words from different resources. We synthesize the pronunciations by G2P model trained with the Phonetisaurus¹⁵ tool.

The ‘spelled acronyms’ like “KLM” (pronounced as “*k ey eh l eh m*”) are treated separately and represented as a single token (e.g., ‘*k_l_m*’). We also add manually created pronunciations for some non-English words that cannot be guessed by the G2P model. All the ‘word tokens’ in the lexicon are in lower-case. We keep only words relevant to ATC domain, i.e. words present in ATC transcripts or other resource. The lexicon contains 29k unique word-symbols.

Our strategy to mitigate the out-of-vocabulary problem is based on enriching the lexicon as much as possible as part of the data preparation. We enriched the lexicon with a list of airline designators for callsigns (partly manually updated)¹⁶. Also, we added all five-letter waypoint¹⁷ names in Europe

¹²Some of these rules and lessons can be easily adapted to other databases in the domain of ASR or NLU.

¹³We use these rules to normalize the transcripts of *UWB-ATCC* and *LDC-ATCC* databases (see Table 1 and 2) for experimentation.

¹⁴Dictionary at: <http://www.speech.cs.cmu.edu/cgi-bin/cmudict>.

¹⁵More information in their GitHub repository: <https://github.com/AdolfVonKleist/Phonetisaurus>.

¹⁶List taken from Wikipedia: https://en.wikipedia.org/wiki/List_of_airline_codes.

¹⁷A waypoint is an intermediate point or place on a route or line of travel, a stopping point or point at which an aircraft’s course is changed.

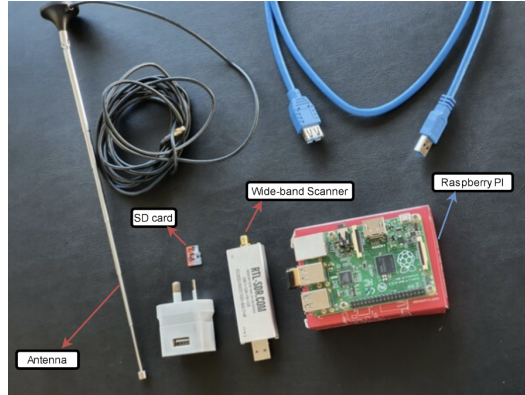


Figure 4: A set of items needed to set up a VHF receiver.

retrieved from open-source project Traffic¹⁸. Finally, we introduced some additional words, such as countries, cities, airport names, airplane models and brands, ATC acronyms, etc.

4 Data Collection

This section describes the collection and pre-processing of the audio data and ATC metadata in the ATCO2 corpus. An overview of the data processing pipeline is given in Figure 2. First, the data is collected via very-high frequency (VHF) radio receivers that are owned by a community of volunteers. Then, the audio and metadata are uploaded to OpenSky Network (OSN) servers¹⁹ via Internet. Finally, the collected data is processed on a ReplayWell server²⁰ via REST API, and part of it is selected for human annotation. The ReplayWell server hosts a major part of the data processing pipeline. We also rely on a community of volunteers for annotation.

4.1 Data Feeders

The data feeders are volunteers who capture ATC voice and upload it to OSN servers. The Data Feeders are typically aviation enthusiasts with possible prior operational experience, or people with an interest in aviation technologies (e.g., people doing domain related research, radio amateurs, etc.). To become a feeder, one needs to own a VHF receiver, which consists of an antenna, software defined radio (SDR) and a computer connected to the Internet. Affordable and popular options such as an RTL-SDR dongle and Raspberry Pi single board computer work sufficiently well in most cases. Quality of recorded ATC data varies depending on the equipment utilized during its collection (properly tuned gain parameter, position of antenna, DSP processor in the radio receiver). As an example, an affordable setup can be built with a *Sirio Md 118-137* antenna and an *RTL-SDR* radio receiver dongle (RTL2832U with 8-bit analog-to-digital converter), this setup is similar to items in Figure 4. For better quality, we recorded with a *Watson WBA-20* antenna and a *SDRPlay - RSP1A* radio receiver, which has a 14-bit analog-to-digital converter.

In some countries, it might be prohibited by law to record air traffic management (ATM) related data. The data feeders should check the applicable regulations before recording and feeding the data to the Internet. If you are interested in becoming a data feeder, please follow the instructions in the ‘feeder zone’ website: <https://ui.atc.opensky-network.org/set-up>

¹⁸Traffic project: <https://pypi.org/project/traffic/>.

¹⁹OpenSky Network is a non-profit association based in Switzerland. It aims at improving the security, reliability, and efficiency of the airspace usage by providing open access of real-world air traffic control data to the public. The OpenSky Network consists of a multitude of sensors connected to the Internet by volunteers, industrial supporters, and academic/governmental organizations.

²⁰The whole pipeline runs live in the following URL: <https://www.spokendata.com/atco2>.

4.2 Data Annotators

The annotators are people who produce transcripts of ATC voice communications. These annotations also include assigning speakers roles and tagging of named entities. During the ATCO2 project, we relied on both the volunteers and paid transcribers. Volunteers with knowledge of ATC phraseology are ideal, but not strictly required.

Currently, we use our data processing pipeline (see Figure 2), which generates the initial transcripts and NLP tags. Pre-transcribing with AI tools speeds-up the overall transcription process. If you are interested in becoming an annotator, please create an account in the SpokenData transcription platform: <http://www.spokendata.com/atco2>. All the transcribed data within ATCO2 project's life was packaged and released as the *ATCO2-test-set corpus*. Both the data feeders and annotators will have access to the data they provided.²¹

4.3 Data Processing Pipeline

The steps from our automatic *data processing pipeline* in Figure 2 are briefly described here:

Segmentation and demodulation: the RTL-SDR radio receiver tuned to a frequency provides a data stream in IQ format. The RTL-SDR software²² has an in-built Voice Activity Detection (VAD) segmentation features. This is based on detecting abrupt changes of energy in the signal. The IQ signal is demodulated into a wave file with *csdr* software.²³ The *csdr* software is configured to remove DC offset, and we don't use automatic gain control. It is important to tune the *gain* parameter in the RTL-SDR software, so the audio is both well audible and not overboosted.

Segment-based gain control: the signal from distant airplanes can be weak. We noticed speaker turns are often separated by spikes in the waveform. The spikes arise from the window-based DC-offset removal in *csdr*. We detect these spikes and increase volume in segments separated by the spikes when needed.

Signal-to-noise ratio filtering: the next processing step is "signal-to-noise ratio filtering". We discard recordings that are too noisy, but audio files with moderate level of noise are not discarded. We use WADA-SNR (Waveform Amplitude Distribution Analysis) [36] to estimate the SNR. WADA-SNR is based on analysis of shape of distribution over samples in a speech waveform. The non-speech parts are removed by a speech activity detection (SAD) tool [37] with a 'tight' preset, leaving almost no non-speech parts marked as speech.

Acoustic-based speaker diarization: a single recording can have multiple speakers in it, so the per-speaker segments are identified by diarization. We do it before the automatic transcripts are generated, so the NLU modules always process segments of a single speaker. Also, the annotators are asked to eventually rectify the per-speaker segments.

For details of the acoustic diarization VBx model, the reader is referred to [38]. This model uses a Bayesian hidden Markov model (BHMM) to find speaker clusters in a sequence of x-vectors. The x-vector extractor uses DNN architecture based on ResNet101 [38]. In the first step, Agglomerative Hierarchical Clustering (AHC) is applied to the extracted x-vectors. Then, Variational Bayes HMM over x-vectors is applied using the AHC output.

Automatic speech recognition: our ASR system has been trained on several publicly available databases [8, 9, 39, 7] and some private databases (AIRBUS, MALORCA). It is a hybrid ASR system trained with Kaldi. The system is covered in more details in Section 6, and also in [2]. The ASR output is confusion network, it is a 'sausage-like' structure with lists of alternate words in bins, and word-confidences in each bin sum up to one.

English language detection: we deployed an *English language detection* system (ELD) to separate non-English utterances from the input stream of data. Specifically, we used an NLP-based system that processes ASR output transcripts with word confidences. This system was more robust and better than standard acoustic-based ELD system [34]. Another benefit from using an NLP system is that it can jointly use logits or probabilities outputs from different ASR systems, which further can boost the results. Our ELD tool was previously covered in [2, 34].

²¹More information on the official Opensky Network website: <https://opensky-network.org>.

²²RTL-SDR radio receiver software: <https://github.com/szpajder/RTLSDR-Airband.git>

²³CSDR software defined radio: <https://github.com/ha7ilm/csdr>

Table 2: Train and test sets configuration for baseline experiments. [†]entire *ATCO2-PL corpus* used for training our ASR modules, see Table 1. [¶]this subset filters out recordings that do not contain speaker role tags (used for speaker role detection). However, we report results on the full *ATCO2-test-set corpus* for the ASR experiments.

Dataset	Statistics			
	Nb. samples [k]	Duration [h]	SNR [dB]	Public
<i>ATCO2-PL-set (train)</i> [†]	3072	5281	any	✓
<i>ATCO2-test-set (test)</i> [¶]	3	3.4	≤15	✓

Post-processing by NLP: in ATCO2 project, we focused on extracting knowledge from the text produced by the ASR system. *ATCO2-test-set corpus* contains rich metadata extracted with different NLP and NLU based modules. Specifically, we performed three tasks:

- *Callsign recognition*: locate the callsign and convert it to code such as "KLM91G"
- *ATCO/pilot classification*: decide who is speaking in the entire utterance
- *ATC-Entity recognition*: highlight the callsign, command and value entities in text

Further details about our NLP/NLU modules are covered in [2]. Information about integration and pre-processing pipeline is in Appendix B.

Dataflow statistics: the statistics for our *data processing pipeline* are accessible in <https://www.spokendata.com/atco2>. The daily numbers summarize the amount of recordings entering the pipeline, being rejected for various reasons (e.g., too low SNR, non-English language detected), being automatically processed, or selected for human annotation.

5 Datasets

Here, we describe in details the datasets for our baseline experiments. We evaluate on the *ATCO2-test-set corpus* as an in-domain test set, and *MALORCA-Vienna test set* as an unseen airport. The baseline systems are trained purely with the *ATCO2-PL-set corpus* and its automatic transcripts (i.e. pseudo-labels).

5.1 ATCO2 databases

ATCO2-test-set corpus: this dataset was built for development and evaluation of ASR and NLP technologies for English ATC communications. The dataset consists of English coming from LKTB, LKPR, LZIB, LSGS, LSZH, LSZB and YSSY airports. We provide two partitions of the data, the *ATCO2-test-set-1h corpus* and the *ATCO2-test-set corpus*. The first corpus contains 1.1 hours of open-sourced transcribed annotations, and it can be accessed for free in <https://www.atco2.org/data>. The latter adds around 3 hours of annotated data and the full corpus will be available for purchase through ELDA in <http://catalog.elra.info/en-us/repository/browse/ELRA-S0484>. The amounts of data per airport are summarized in Table 4. The recordings of both corpora are mono-channel sampled at 16kHz and 16-bit PCM. An example of the XML format for transcripts and tags is in Appendix D.

ATCO2-PL-set corpus: ATCO2 project recorded a large database of ATC voice communications. Altogether, we collected over 5281 hours of ATC speech from different airports around the world (see Table 3). In total, we cover ten airports. Table 3 depicts all this metadata per airport, further split by English language score. To the best of the author’s knowledge, this is the largest and richest²⁴ dataset in the area of ATC ever created that is accessible to the public. The automatic transcripts are stored as confusion network, stored as a *ctm* text format extended to have more words per line (confusion network bin):

<wav-id> <speaker> <t_begin> <dur> <word1> <conf1> <word2> <conf2> ...

²⁴By richest, we mean quality of annotations and amount of metadata per sample. Also, this is the first public database in the area of ATC that targets NLU tasks.

Table 3: Stats about the collected databases per airport. Duration, SNR, language scores and contextual data columns report the mean and standard deviation (mean/std) per sample. Each recording/sample contains one or more segments (we provide timing information in RTTM format). [†]abbreviation in IETF format. ^{††}total number of segments and accumulated duration of speech (after voice activity detection) per airport.

Database		Metadata				Contextual data	
ICAO - Airport	Accent [†]	# Segments ^{††}	Dur. [sec]	SNR [dB]	Lang Score	# n-grams	# entities
<i>English Data (language score ≥ 0.5)</i>							
EETN - Tallinn	et	79 k/131 hr	6.0/3.4	4.6/7.8	0.96/0.08	104/26	37/9
EPLB - Lublin	pl	<1 k/<1 hr	13.3/8.0	2.5/8.2	0.94/0.11	19/10	4/2
LKPR - Prague	cs	999 k/1762 hr	6.4/4.3	14.2/8.2	0.95/0.09	230/95	70/30
LKTB - Brno	cs	401 k/888 hr	8.0/14.4	4.1/15.7	0.88/0.15	49/35	15/10
LSGS - Sion	fr-ch	168 k/330 hr	7.1/4.8	10.0/8.0	0.87/0.15	56/23	20/8
LSZB - Bern	gsw	324 k/699 hr	7.8/5.0	15.4/10.7	0.9/0.13	101/42	36/15
LSZH - Zurich	gsw	470 k/921 hr	7.0/4.6	7.8/7.7	0.94/0.1	526/179	169/55
LZIB - Bratislava	sk	9 k/24 hr	8.8/6.9	5.4/8.7	0.86/0.15	68/27	22/8
YBBN - Brisbane	en-au	105 k/170 hr	5.8/4.1	10.2/5.8	0.93/0.1	268/86	95/30
YSSY - Sydney	en-au	49 k/77 hr	5.7/9.2	3.1/7.0	0.92/0.11	495/148	174/52
others - others	others	<1 k/<1 hr	5.0/6.7	4.0/7.4	0.92/0.11	55/260	16/78
<i>Non-English Data (language score < 0.5)</i>							
EETN - Tallinn	et	2 k/2 hr	4.0/2.4	2.9/10.8	0.3/0.14	95/30	33/11
EPLB - Lublin	pl	<1 k/<1 hr	13.1/2.7	-8.4/12.8	0.2/0.13	17/7	4/1
LKPR - Prague	cs	105 k/187 hr	6.4/5.4	13.8/9.3	0.18/0.16	217/97	67/30
LKTB - Brno	cs	214 k/611 hr	10.3/19.2	6.5/11.8	0.15/0.15	56/33	18/10
LSGS - Sion	fr-ch	57 k/83 hr	5.3/3.6	9.8/9.3	0.27/0.14	56/25	20/8
LSZB - Bern	gsw	42 k/55 hr	4.7/3.4	13.6/13.9	0.3/0.13	102/45	37/16
LSZH - Zurich	gsw	36 k/49 hr	5.0/4.1	2.0/12.7	0.25/0.15	485/180	157/56
LZIB - Bratislava	sk	10 k/26 hr	9.0/7.6	7.1/7.0	0.18/0.15	72/26	23/8
YBBN - Brisbane	en-au	7 k/10 hr	4.9/4.8	5.9/12.3	0.24/0.16	268/79	95/28
YSSY - Sydney	en-au	3 k/3 hr	3.9/2.3	2.7/10.5	0.33/0.13	481/151	169/53
others - others	others	<1 k/<1 hr	5.2/6.4	3.7/9.0	0.26/0.15	0/0	0/0

Table 4: ATCO2-test-set corpora split by airports.

ICAO - Airport	ATCO2-test-set		ATCO2-test-set-1h	
	sentences	words	sentences	words
LKPR Prague	207	2686	102	1254
LKTB Brno	60	854	32	451
LSGS Sion	932	10183	256	2684
LSZB Bern	452	5908	172	2323
LSZH Zurich	640	8123	126	1764
LZIB Stefanik	165	2256	79	1051
YSSY Sydney	1065	10434	102	1058
Sum	3521	40444	689	10585

342 LKPR_Tower_134_560MHz_20211223_154543 A 1.25 0.10 the 0.845 papa 0.042 ...

343 Another view of the data is in Figure 5, where we don't split by the English detection score. The
344 distributions are from the full, 5281 hours dataset. In sub-figure 5a, we see that the majority of data
345 was recorded in Prague, Brno, Zurich, Bern, and Sion airports. This is because we started recording
346 these airport's data early in the ATCO2 project. Next, we also have some data from Brisbane, Talinn,
347 Sydney, Bratislava (STEFANIK) and Lublin. In 5b, we see that majority of our data has high English
348 scores (the dashed line 'ALL DATA'). There are some airports that have more non-English utterances:
349 Brno, Bratislava (STEFANIK). And there are some airports, for which the distribution is more
350 uniform than for others: Sion. We know for sure that local language is present at higher quantities in
351 the data from Brno, Bratislava and Sion airports. And bigger airports usually have a policy to speak
352 only in English, which explains low number of detections of non-English speech there. From 5c we
353 see that levels of noise differ across the airports. The cleanest signal is for Prague and Bern, while
354 high levels of noise are from Sydney and Lublin, and some noise also for Tallinn and Bratislava. This
355 indicates that the recording setup could be improved. And in 5d are the distributions of confidences

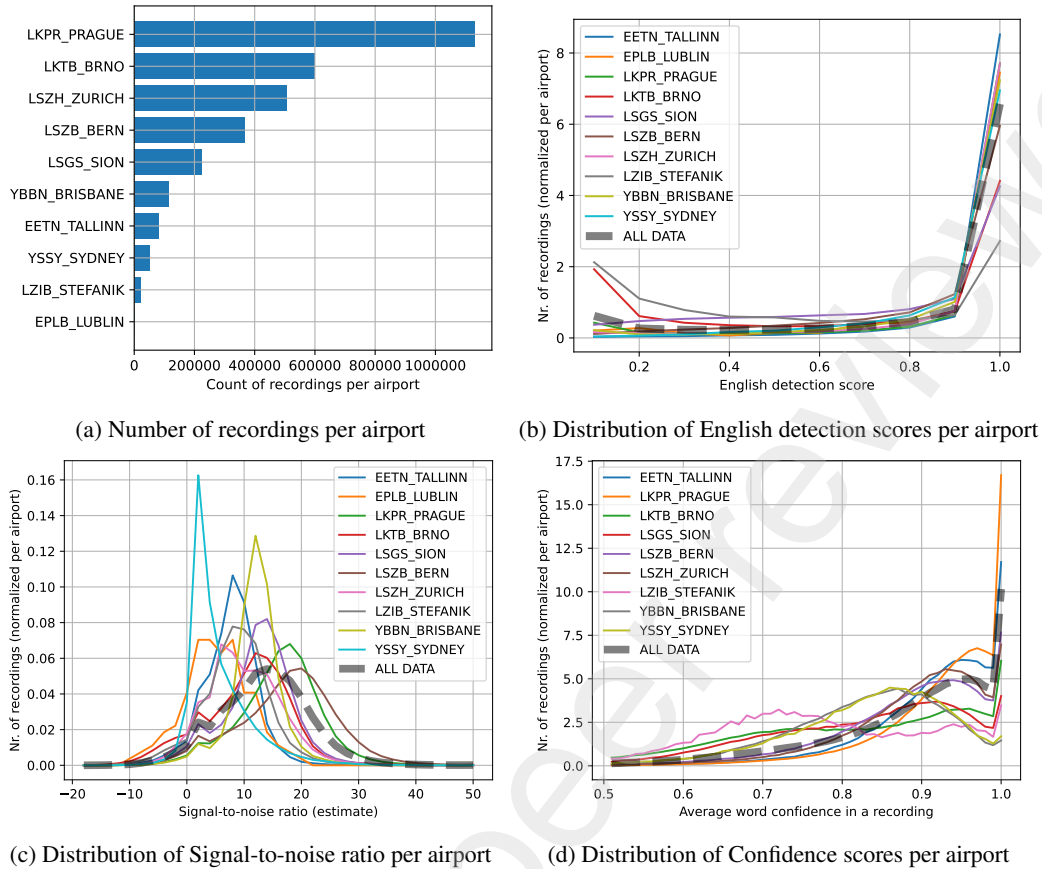


Figure 5: Distribution plots of metadata for *ATCO2-PL set corpus*.

of the automatic transcripts, assigned by the seed ASR system. Majority of the probability mass is in interval (0.8, 1.0) (dashed curve 'ALL DATA'). The highest confidence is assigned to Prague data (highest peak on right). The lowest confidence have the data from Bratislava, Brisbane and Sydney airports (distributions with leftmost modes). The higher tails with lower confidences are very likely caused by the non-English speech and noisy signal in the data.

5.2 Private Databases

MALORCA Vienna test set: The MALORCA Vienna test set is used in baseline ASR experiments as an unseen airport. No Vienna data are in the *ATCO2-PL-set* that use for training the acoustic model and language model. On the other hand, MALORCA Vienna data were present in the training of the seed system for generating the automatic transcripts. So it both unseen and indirectly seen at the same time. The set consists of ATCO speech only, which normally has lower error rates than the pilot speech [30, 40]. The total amount of speech after VAD is 1.9 hours. The audio data is mono-channel sampled at 8kHz and 16-bit PCM.

6 Automatic Speech Recognition

The Automatic Speech Recognition (ASR) system has an audio signal as its input and produces text transcripts as its output.

At first, we trained a 'seed ASR system' from several existing ATC databases. The seed ASR system is part of the 'data processing pipeline' (see Section 4.3). This ASR produced the automatic transcripts for the *ATCO2-PL-set corpus* and also the initial transcripts for the *ATCO2-test-set corpus*

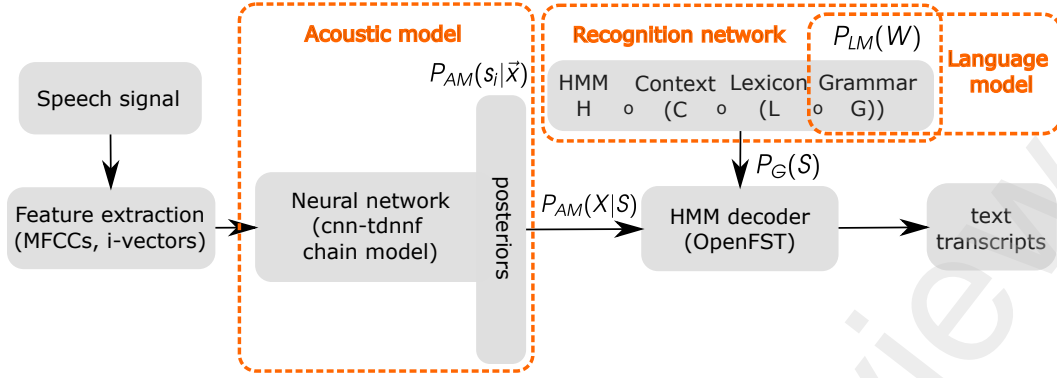


Figure 6: Hybrid-based ASR system. The inference pipeline consists of *feature extraction*, *acoustic matching* by acoustic model and *search* by HMM decoder that uses HCLG recognition network. On the output are text transcripts. Alternatively, the output can be a *lattice* (a graph with alternative decoded paths) or *confusion network* (time-sequence of bins with word-lists having scores).

375 that were manually corrected. During the ATCO2 project, we worked mainly with hybrid-based ASR
376 systems, trained with the open-source toolkit Kaldi [41].

377 In hybrid speech recognizers, Hidden Markov Models support various speech rates, by allowing to
378 "stay in a state" for some time via self-loop transitions. The acoustic scores come from a neural
379 network, and the decoding process is based on searching in the matrix of acoustic scores for state-
380 sequences with plausible transcriptions generated from a pre-compiled recognition network HCLG
381 (i.e., a large HMM graph/model). Thus, HMMs provide a structure for mapping a temporal sequence
382 of acoustic scores into a sequence of states [42, 43], from which the recognized words are extracted.

383 Inference in a hybrid speech recognizer has three stages: **feature extraction**, **acoustic matching** and
384 **decoding**, the overall scheme is in Figure 6.

385 **Feature extraction** compresses the waveform into a sequence of fixed-length vectors of low dimen-
386 sion, in our recipe we use high-resolution MFCCs with i-vectors [44] appended.

387 **Matching of acoustic units** by acoustic model converts the input features into posterior probabilities
388 of a closed set of acoustic units (phoneme states), whose time series forms the acoustic score matrix.
389 In our recipe, we use 'chain' model neural network (NN) trained by Lattice-free MMI [45]. The NN
390 topology is 'cnn-tdnn' architecture with 6 conv-relu-batchnorm-layer components followed by
391 9 tdnnf-layer components [46], and 2 softmax layers with 2000 outputs each. The acoustic model
392 consists of 12.9 million trainable parameters.

393 **Decoding** searches for the most likely word sequence \hat{W} (transcription), in the matrix of acoustic
394 scores. The search explores HMM paths that exist in a recognition network, termed HCLG graph.
395 The standard decoding algorithm is based on two ideas: *token passing* and *beam search*. The search
396 combines scores from the acoustic model, language model and lexicon, as shown in equation (1) :

$$\hat{W} = \text{wrds} \left(\underset{S}{\operatorname{argmax}} P_{AM}(S|\mathbf{X})^\kappa P_G(S) \right) . \quad (1)$$

397 The acoustic model scores are the chain model posteriors $P_{AM}(S|\mathbf{X})$, where \mathbf{X} is the time-series
398 of input features and S is an HMM state-sequence. The language model and lexicon scores are
399 both represented in the graph score $P_G(S)$ that is present in the HCLG recognition network. κ is
400 an empirical scaling constant, for chain models the optimal $\kappa = 1.0$. And the function $\text{wrds}(\cdot)$ is
401 reading word-sequence from the state sequence S with the maximal score.

402 **The HCLG graph** is a Weighted Finite State Transducer (WFST). The HCLG graph is composed of
403 a language model graph G , pronunciation lexicon graph L , context dependency graph C and phoneme
404 HMM graphs H . The HCLG graph contains graph costs P_G that originate from its source graphs,
405 while the most important source is the language model. This was the description of a hybrid ASR
406 system.

The other type of ASR systems are End2End systems. The End2End systems do not rely on HMMs and do not have a pronunciation lexicon. However, End2End systems require more training data to achieve good performance. Hybrid systems remain one of the best and more flexible approaches for building ASR engines. The HMM-DNNs based ASR are used in the current state-of-the-art systems for ASR in ATC communications [29, 28, 4, 3].

Hybrid-based ASR systems train independently the Acoustic model and the Language model. the language model is trained on a text corpus. This allows to incorporate text resources without the necessity to have the corresponding audio. The hybrid ASR relies on a word-based lexicon, and words that are not in the lexicon or language model cannot be hypothesized by ASR decoder (Out-of-vocabulary word problem – OOVs).

We use the same ASR system both for ATCOs and pilots. The training recipe and databases for our ‘seed ASR system’ (including the train sets in Table 1) are covered in [2, 3, 4, 47]. Briefly, we used AIRBUS, MALORCA Vienna, ATCOSIM, UWB-ATCC, LDC-ATCC, HIWIRE and N4-NATO databases. In total, these form a database of ≈ 135 hours. We augmented this database with noises captured from LiveATC. And the data were further augmented by speed perturbation. Due to data license issues with some databases, this ASR system can be only used for research.

In a later stage of the ATCO2 project, we experimented with **contextual adaptation** and **semi-supervised training**. We later integrated these technologies into the ‘seed ASR system’.

The **contextual adaptation** improves the accuracy of the ASR system by feeding-in a rapidly changing contextual information. Based on surveillance data, we suggested a list of nearby callsigns into the recognizer [48]. This was done by applying a boosting WFST graph to HCLG or lattice. In HCLG boosting, we give score discounts to individual words, while in Lattice boosting, the score discounts are given to word sequences. The lattice boosting was used also when generating the automatic transcripts for *ATCO2-PL-set corpus*. Also, in [49, 50] lattice boosting and language model boosting are explored.

The **semi-supervised training** was used to improve ASR accuracy by retraining the acoustic model [2] on a mixture of manually and automatically transcribed data. ATCO2 data with automatic transcripts were mixed with transcribed data from other databases. We used per-frame gradient weighting by word confidences to de-weight data with unreliable transcripts. We further performed experiments in [47]. Here, we applied callsign boosting when generating automatic transcripts for semi-supervised learning, and we obtained 17.5% relative WER improvement measured on the callsign words.

6.1 Baseline experiments

During the ATCO2 project, we collected 5281 hours of ATC audio data from several airports. We processed the data with our automatic pipeline (see Figure 2) that filters the data and produces automatic transcripts. Inside the pipeline, there is an ASR system that is described in Section 6 and also in our previous work [2].

The purpose of these baseline experiments is to demonstrate what can be achieved with the data we collected and released in ELDA catalogue. From these automatic transcripts, we can bootstrap and build a new ASR system, without having licensing problems that exist for some other databases (Table 1). We built a new language model from all the generated transcripts. And, we experimented with training acoustic models on various subsets of the audio data. We re-used the lexicon from the ‘seed ASR system’.

The baseline experiments are described in Table 5, where we computed Word Error Rate (WER) on three test sets: *ATCO2-test-set*, *ATCO2-test-set-1h* and *MALORCA Vienna* test set. Each model is tagged with the number from the first column of Table 5. The MALORCA Vienna test set represents clean ATCO speech from an unseen airport.

Analysis of ASR systems from Table 5: In 1) we built the acoustic model and language model on all the data in the ELDA package, including the data that the English detector identified as non-English. In 2) we excluded the non-English data, and from now on, the Language Model is always trained from transcripts of this 4500 hours dataset (except for seed system). In 3) we set the filtering thresholds higher to >0.7 ELD (English detection), >0 dB SNR and >0.8 CNET score (average word confidence in a confusion network of recording). In WER results for 1) 2) 3), we see that the *ATCO2 test sets* results stay similar, while the WER for MALORCA test set improves with stronger data filtering. In

Table 5: Performance on *ATCO2-test-set corpus*. The ASR system is built from the automatic transcripts of the *ATCO2-PL-set corpus*. We use two *ATCO2-test-set corpus* splits, and MALORCA Vienna [28, 29] as an unseen airport. The data filtering is done according to: ELD (English language detection), SNR (signal-to-noise) ratio, and CNET (average word confidence in the recording).

System	Training hours	WER			Data Selection Method			
		ATCO2 test-set (4h)	ATCO2 test-set 1h	MALORCA Vienna	ELD	SNR	CNET	Note:
1)	5281	22.3	15.8	11.1	any	any	any	all ATCO2 data
2)	4500	22.5	15.7	10.0	>0.5	any	any	remove non-English
3)	3600	22.5	15.8	9.3	>0.7	>0	>0.8	remove low-confidence
4)	1500	23.4	16.7	11.9	>0.5	>16	any	remove low SNR (<16)
5)	3600	22.4	15.4	9.0	>0.5	any	any	random from 4500 hour set
6)	2500	22.6	15.8	9.0	>0.5	any	any	random from 4500 hour set
7)	1500	22.5	15.8	10.6	>0.5	any	any	random from 4500 hour set
8)	500	22.5	15.7	11.0	>0.5	any	any	random from 4500 hour set
9)	135+700	26.6	18.6	4.8	-	-	-	seed system

460 4) we realized that it is not a good idea to discard too much noisy data by filtering >16 SNR. Next, in
461 5) we randomly selected 3600 hours from the 4500 hours dataset. This was to cross-check with the
462 filtering we previously used in 3). To our surprise, the results are marginally better when randomly
463 selecting the data. Next, in 6) 7) 8) we continued randomly selecting subsets from the 4500 hours
464 dataset. This degraded the performance of MALORCA Vienna on 7) 8) by up to 2% WER. From the
465 results, we notice that WER for ATCO2 test-sets is nearly constant, except 4). It seems that WER in
466 the automatic transcripts is an important factor. The automatic transcripts are used as training targets,
467 and the WER in transcripts pre-determines the performance of the trained system. The amount of
468 training data is possibly less important, however the generalization to a new airport (MALORCA
469 Vienna) is better with larger volumes of training data of 2500 or 3600 hours in ASR systems 5) 6).
470 For completeness, we also add WER of the seed system 9). The seed system had few percent higher
471 WER for ATCO2 test-sets. For MALORCA Vienna, the seed system works as good as 4.8% WER,
472 as MALORCA Vienna corpus was present in its training data.

473 7 Natural Language Processing and Understanding

474 Until the previous decade, research on ATC was directed at only transcribing as accurate as possible
475 the dialogues between ATCOs and pilots. However, transcription is only one part of the story and
476 further information, such as, entity highlighting (also known as intent and slot filling) or speaker
477 role detection is imperative in real-life ATC control rooms. The process of parsing these high-level
478 entities from ATC audio can be seen as SLU, or from text as NLU.

479 Previous work has already explained several NLP tasks in the area of ATC. For instance, [51] describes
480 a set of entities and elements that are present in ATC communications that are of special interest, e.g.,
481 commands and instructions. The authors advise that a real-life system should be composed of an
482 ASR module to obtain the word-level transcripts of the communication. Later, a subsequent system
483 should extract ATC-related key entities and then parse them into a specific grammar. We redirect the
484 reader to [35], which developed an ATC-structured grammar accepted by several European institutes.
485 Furthermore, in [51], the process of extracting key entities from audio is summarized in an entire
486 pipeline composed of three submodules. Namely, speaker role detection, intent classification and,
487 slot filling (analogous to NER but on audio level). They aim at inferring the near-future air traffic
488 dynamics, which can aid ATCOs in their daily task. In addition, this system can notice communication
489 errors caused by one of the speakers, also known as hear or read back errors. Some exploratory
490 work addressing NLP and NLU on the framework of HAAWAI and ATCO2 projects (see Table 1) is
491 described in [52, 17].

492 In this section, we describe our baselines for two tasks related to NLP and NLU.²⁵ In ATC, in addition
493 to transcripts generated by an ASR system, we can also extract rich metadata from the transcripts and
494 audio. Some examples are (but not limited):

²⁵As we work on top of ASR transcripts, these tasks can be also cataloged as spoken language understanding.

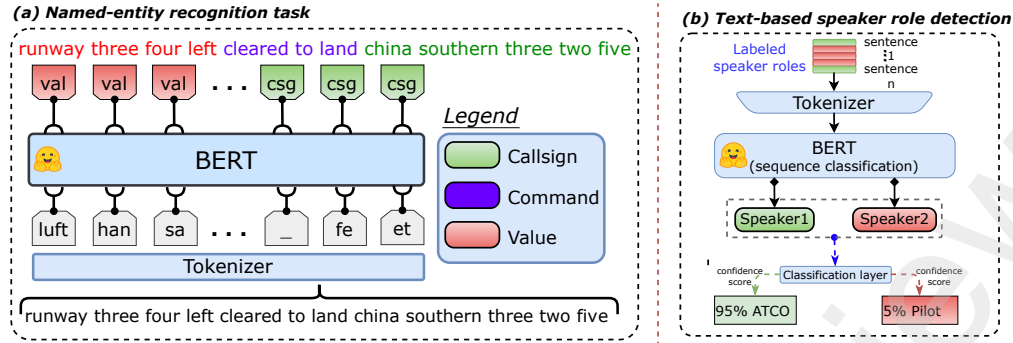


Figure 7: (a) Named entity recognition and (b) speaker role detection based on sequence classification (SC) for ATC utterances. Both systems are based on fine-tuning to ATC tasks from a pre-trained BERT [54] model. The NER systems recognizes callsign, command and values, while the SC assigns a speaker role to the input sequence.

- 495 • ✓ What are the high-level entities in the communication? → named-entity recognition
496 (NER) or slot filling (SF). Previous work in [49] and covered in Section 7.1,
- 497 • ✓ Who is talking? ATCO or pilot → speaker role detection (SRD), sequence classification.
498 Early work on [52], and covered in Section 7.3,
- 499 • ✗ Is the pilot responding the correct information? → read-back error detection. Our
500 previous work in [53],
- 501 • ✗ Is the communication being uttered in English language? → English language detection
502 (ELD). Our previous work in [34].

503 We present baselines only on the above items marked with ✓, while the items marked with ✗
504 are, either, covered in previous work or are left as future research directions. Generally speaking,
505 extracting the above-mentioned information could allow to further fulfill other ATC tasks, e.g.,
506 pre-filling radar labels in the ATC control room. Or, for example, decrease the workload of ATCOs
507 and increase their efficiency by automating manual and effortful processes. In addition, reducing the
508 overall probability of incidents and accidents due to air traffic management erroneous procedures is a
509 supplementary by-product of introducing AI tools in the ATC control rooms.

510 7.1 Named Entity Recognition

511 Named entity recognition, or NER, is one of the most explored tasks in the field of information
512 extraction and NLP [55]. NER aims to locate and classify entities in unstructured text into pre-
513 defined classes or categories. Examples are, persons or organization names, expressions, or, for
514 instance, callsigns or commands in ATC. Initially, NER was based on handcrafted lexicons, ontology,
515 dictionaries, and rules [56]. Even though these systems were interpretable and understandable, they
516 were prone to human errors. Collobert et al. [57] introduced machine learning-based methods for
517 text processing in topics such as part-of-speech tagging, chunking, NER, and semantic role labeling.
518 Further interesting works on NER are [58] focusing on multilingual NER for slavic languages, and
519 [59] presenting a broad survey of NER methods. In practice, a NER system can be crafted by
520 fine-tuning a pre-trained LM, e.g., BERT [54], RoBERTa [60], or DeBERTa [61]. Nonetheless, these
521 models are data hungry and need expensive GPUs during its training and inference. Further work
522 has been directed at reducing their computational footprint, by performing, for example, knowledge
523 distillation [62].

524 Air traffic control communications typically carry structured information, including callsigns, com-
525 mands and values. These can be seen as ‘named entities’. *ATCO2-test-set corpus* provides annotation
526 on the word level that assigns pieces of text to these specific classes. We developed a baseline system
527 to extract such information from ASR utterances, as depicted in Figure 7. An early implementation
528 of this system was covered in [49]. However, these experiments were carried over private databases,
529 so it is difficult to compare with our current results. That is why we base our experiments in [49], but
530 we go beyond by open sourcing scripts to fine-tune a NER model with *ATCO2-test-set corpus*.

7.1.1 Experimental Setup

Our experiments are carried out with *ATCO2-test-set corpus* only, for both, training and evaluation.²⁶ The main reason is that none of the public databases from Table 1 contain NER annotations. As a workaround, we implemented a simple k-fold cross-validation scheme. We define $K = 5$ folds, with a 70/10/20 ratio for train/dev/test subsets, respectively. We use ground truth ASR transcripts for training and testing NER.

First, we download a powerful pre-trained LM, BERT²⁷ [54], from HuggingFace [63, 64]. We append a linear layer with a dimension of 8 (following the IOB format, i.e., two outputs for each NER class) on top of the last layer of the BERT model. The model is later fine-tuned on the NER task, with each Fold K of the train splits. Each model is fine-tuned on an NVIDIA GeForce RTX 3090 for 10k steps. During experimentation, we use the same learning rate of $\gamma = 5e-5$ with a linear learning rate scheduler. Dropout [65] is set to $dp = 0.1$ for the attention and hidden layers, while Gaussian Error Linear Units (GELU) is used as activation function [66]. We also employ gradient norm clipping [67]. We fine-tune each model with an effective batch size of 32 over 50 epochs with AdamW [68] optimizer ($\beta_1=0.9$, $\beta_2=0.999$, $\epsilon=1e-8$).

7.1.2 Results

We report the results obtained from the 5-fold cross validation experiments. We split the results by tags, namely, callsign, command and values. For each of them, we report precision, recall and F1-scores in Table 6. We obtained an average of 0.97, 0.82 and 0.87 F1-score for callsign, commands and values. We observed that the command class was the most challenging among the three classes. We believe this is because commands contain extra complexity in comparison to callsigns and values. For example, in some cases the ATCOs or pilots use several commands, or these are sometimes mixed in the same utterance. In contrary, callsigns follow a standard form, composed of an airline designator, numbers, and letters (spelled in ICAO phraseology). Values are composed of cardinal numbers and some standard words, e.g., ‘flight level’. We also noted a significant irregularity in performance for the command class between the 5 folds (see column: Command in Table 6). For example, worse \rightarrow best scenario on F1-score was 0.79 \rightarrow 0.85, almost a six-point drop. A five-point drop is also seen in precision and recall. These results are seen when comparing fold 2 (best) against fold 4 (worst).

In conclusion, the results from Table 6 are the first official baseline for NER²⁸ on the *ATCO2-test-set corpus*. However, there is room for improvement. For instance, implementing semi-supervised learning or data augmentation should bring robustness and yield higher performance. Similarly, one can pretrain the LM directly on ATC text rather than standard English text, which should bring in additional benefits. We leave this line of research for future work.

7.2 Callsign Recognition and Understanding

The Named Entity Recognition from previous section is capable to select words which form a callsign (i.e., highlight ‘swiss two six eight nine’). However, *ICAO Callsign Extraction* produces callsign directly in ICAO format (e.g., SWR2689), which is more useful for applications. This is not trivial because callsigns get commonly shortened, if the situation is obvious (e.g., ‘swiss two six eight nine’ \rightarrow ‘six eight nine’, or ‘swiss eight nine’). And the underlying ASR produces errors in its automatic transcripts.

In the project, we explored two approaches. In [69], the ICAO callsign is retrieved by a BERT-based Encoder-Decoder neural network. This system directly takes outputs from an in-domain ASR system and extracts the ICAO callsign without relying on Named Entity Recognition as an intermediate step. The model uses a list of callsigns from surveillance data as context information, and it can return an ICAO callsign that is not present in the list. The overall approach is depicted in Figure 8.

The second approach [49] performs NER to extract the callsign within the sentence, which is later ranked by Levenshtein distance with the ones in the callsign list from the surveillance data.

²⁶We provide in the GitHub repository the utterance IDs splits utilized for these experiments.

²⁷We use the pre-trained version of bert-base-uncased with 110 million parameters for all the experiments.

²⁸After extensive research, to authors’ knowledge, this is the first official baseline on NER for air traffic control communications. We have not found any other work that is, both open-source and that targets NER.

Table 6: Different performance metrics for callsign, command and values classes of the NER system. Metrics reported for each of the 5-fold cross-validation scheme on *ATCO2-test-set corpus* with a bert-base-uncased model. @P, @R and @F1, refers to precision, recall and F1-score, respectively. Numbers in **bold** refers to the top performance per column among folds. [†]mean score over the 5 folds.

Fold	Callsign			Command			Values		
	@P	@R	@F1	@P	@R	@F1	@P	@R	@F1
1	0.97	0.98	0.97	0.80	0.81	0.81	0.86	0.86	0.86
2	0.97	0.98	0.97	0.83	0.86	0.85	0.86	0.89	0.87
3	0.97	0.97	0.97	0.81	0.85	0.83	0.87	0.87	0.87
4	0.98	0.98	0.98	0.78	0.80	0.79	0.85	0.90	0.87
5	0.97	0.98	0.98	0.80	0.83	0.81	0.87	0.89	0.88
AVG [†]	0.97	0.98	0.97	0.80	0.83	0.82	0.86	0.88	0.87

579 This approach always selects a callsign from the list. We showed that boosting callsigns with the
580 combination of ASR and NLP methods eventually leads up to 53.7% of an absolute, or 60.4% of a
581 relative, improvement in callsign recognition.

582 7.3 Speaker Role Detection

583 In NLP, text classification or sequence
584 classification (SC) is a task that as-
585 signs a label or a class to a sequence of
586 words [70, 71]. The hypothesis is that
587 the words within the given text share
588 a common role and meaning inside
589 the sentence’s grammatical structure.
590 One of the most acknowledged forms
591 of SC is sentiment analysis, which as-
592 signs a label like positive, negative, or
593 neutral to a sequence of text embed-
594 dings²⁹ [73]. Nowadays, state-of-the-
595 art SC systems are based on the well-
596 known Transformer, e.g., BERT [54]
597 or RoBERTa [60]. Akin to NER, SC
598 is considered a downstream task oper-
599 ating on ASR output.

600 In ATC, the dialogues are built on top
601 of a well-defined lexicon and dictio-
602 nary, which follows a simple grammar.
603 This standard phraseology has been
604 defined by the ICAO [1] to guarantee
605 the safety and reduce miscommunications between the ATCOs and pilots. In this work, we pro-
606 pose some baselines on the SC task aimed at detecting the speaker role from transcribed ATC
607 communications (sentences). Our previous work on speaker role detection is covered in [17, 52].

608 7.3.1 Experimental Setup

609 The SC experiments are carried out in a very related manner to NER (see Section 7.1.1). Specifically,
610 we use the same model (bert-base-uncased), hyperparameters (e.g., number of epochs), optimizer,
611 dropout rates and so on. However, here, we fine-tuned the model on the SC task rather than NER. We
612 append a linear layer with a dimension of 4 (following the classes structure from Section 3.2 of [49])
613 on top of the last layer of the BERT model, i.e., a two-class classification model.

²⁹However, a sequence of acoustic embeddings can also be used for SC, e.g., emotion classification in raw speech [72].

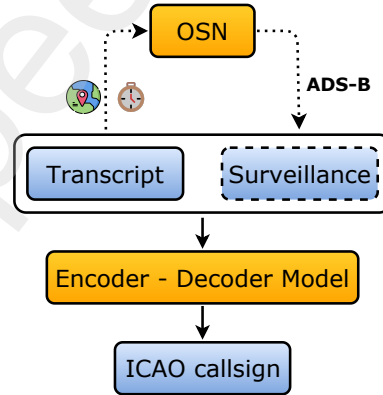


Figure 8: Proposed callsign recognition and understanding system. The dotted path marks the optional surveillance retrieval via OSN with the aid of the transcripts timestamp and VHF receiver location. Taken from [69].

Table 7: Different performance metrics for the speaker role detection experiments. Metrics reported on *ATCO2-test-set corpus* with a *bert-base-uncased* model trained on the splits from Table 2. @P, @R and @F1, refers to precision, recall and F1-score, respectively. Numbers in **bold** refers to the top performance per column.

Training Corpus	ATCO			PILOT			AVG
	@P	@R	@F1	@P	@R	@F1	@F1
LDC-ATCC	0.87	0.73	0.79	0.70	0.86	0.77	0.78
UWB-ATCC	0.88	0.83	0.86	0.80	0.85	0.82	0.84
LDC-ATCC + UWB-ATCC	0.92	0.78	0.85	0.76	0.91	0.83	0.84

We employed LDC-ATCC³⁰ and UWB-ATCC³¹ datasets (see Table 1) for fine-tuning and *ATCO2-test-set corpus* for testing. In LDC-ATCC and UWB-ATCC databases, speaker roles tags for each sample are marked in the original transcripts. And, we use ground truth ASR transcripts the evaluation. We create speaker-independent train/test splits based on the original databases. The split IDs for each subset are registered in the public GitHub repository of this paper.

7.3.2 Results

We report the baseline results for speaker role detection in Table 7. Differently from NER, we only used *ATCO2-test-set corpus* for evaluation. We trained three models using different training datasets. From Table 7 we can see that pilots' communications are more challenging for our model in comparison to the ones from ATCOs. For instance, in the model fine-tuned with LDC-ATCC corpus, there is a two-point drop in F1-scores for pilots, i.e., $0.79 \rightarrow 0.77$ F1-score. Similar behavior is seen in the model fine-tuned with UWB-ATCC corpus, i.e., a four-point drop in F1-scores, $0.86 \rightarrow 0.82$. However, models trained on the later show more robustness for both classes in comparison to the one trained with LDC-ATCC.

We also investigated the performance benefit of combining both datasets. For this experiment, we only obtained one point increase for the pilot class, while one point decrease for the ATCO class, both in comparison to the model trained on UWB-ATCC only. It is important to keep in mind that *ATCO2-test-set corpus* is a completely unseen dataset throughout all the experiments. We are convinced that integrating a small in-domain development set could boost the performances.

8 Legal and privacy aspects for collection of ATC recordings

In order to safely distribute and make available the ATCO Corpus to the community, we took into account legal and ethical considerations as a prerequisite to distribute this content both, commercially and as open-source package. The main question we faced was to determine whether we could legally record and distribute ATC. To answer that question, we inquired into how legislation and regulations treat ATC [74].

Our first hypothesis was that ATC would fall under the rules of Intellectual Property law which regulate how authors and companies can collect and use immaterial works such as recordings, where we believed ATC could fall into. To confirm this hypothesis, we aimed to find out whether ATC could be considered as material that could be protected by intellectual property legislation. Therefore, we performed a thorough study of the two major legal intellectual property systems of the United States and Europe. This study showed that due to the specific characteristics of ATC, such as phraseology and context, these conversations could not be protected as such as they do not meet the originality threshold for protection.

³⁰The Air Traffic Control Corpus (LDC-ATCC) corpus is public in: <https://catalog.ldc.upenn.edu/LDC94S14A>. It comprises recorded speech for use in the area of ASR for ATC. The audio data is composed of voice communication traffic between various controllers and pilots.

³¹The UWB-ATCC corpus is released by the University of West Bohemia, and it can be downloaded for free in: <https://lindat.mff.cuni.cz/repository/xmlui/handle/11858/00-097C-0000-0001-CCA1-0>. The corpus contains recordings of communication between ATCOs and pilots. The speech is manually transcribed and labeled with the speaker information, i.e., whether ATCO or pilot is speaking and when.

647 Then we moved on to another hypothesis. We thought that even if these conversations can not be
648 protected as such, they might be protected as part of databases collected by either aircraft companies
649 or Air Navigation Services Providers (ANSPs). As part of our investigations, we came into contact
650 with some of these stakeholders, but none of them replied favorably to our requests. For example,
651 the National Air Traffic Services which handles the airspace for the United Kingdom replied to us
652 that they could not provide their recordings unless mandated by a Court order. Moreover, the United
653 Kingdom is one of the few countries that expressly prohibit recording ATC communications, as its
654 legislation strictly prohibits the use of unlicensed recording apparatus³².

655 Other countries have a more lenient policy towards access and recording of ATC. Indeed, during our
656 research we found out that ATC recorded in the US could be accessed on demand by formulating a
657 request to the Federal Aviation Administration (FAA, hereafter). This is made possible by the use of
658 the Freedom of Information Act (FOIA) that compels US administrations to make available certain
659 types of information collected by these administrations during their operations. In the specific case of
660 the FAA, Freedom of information regulations states that radio and computer data can be obtained
661 upon request as stated in Chapter 4 Section 4-8-2 of the Facility Operation and Administration Order
662 ³³. Nevertheless, during our exchanges with the FAA we found out that requests for audio files needed
663 to concern the last 45 days as required by Chapter 12, section 2 Article 12-2-2 of the same order and
664 had to be specific to an airport in order to be processed adequately by the administration. Future work
665 may include the drafting of such a request to confirm the reality of those conversations.

666 For the airports based in Europe, we based our collection process on the existence of the Open
667 Data Directive, formerly known as the Public Sector Directive, whose goal is to allow reuse and
668 redistribution of data collected by public services, as we found out, many ANSPs are either State-
669 owned or run by state administration for obvious security reasons. Therefore, we made a request
670 in France to access data collected by the administration in charge of Air Traffic Control. We based
671 our request on the provisions of French Law allowing to request the access to data produced by this
672 administration. Regarding ATC, our request went up to the Commission d'Accès aux Documents
673 Administratifs (Commission for access to administrative documents). This Commission ruled that
674 the Direction Générale de l'Aviation Civile (DGAC) did not have to fulfill our request for data since
675 they could not differentiate between civilian and military aircraft and that the recordings could leave
676 the identification of speakers. However, following an *a contrario* interpretation, it can be assumed
677 that since our project focussed on civilian aircraft and that we ensured the anonymization of the
678 conversations before making them available, we could pursue data collection.

679 This previous ruling raised our concerns regarding the compliance of the project especially with
680 the regulations related to protection of personal data, especially the EU General Data Protection
681 Regulation (GDPR). GDPR is the main text regulating the collection and distribution of databases
682 containing personal data. In the case of ATC, the speech data contains voiceprints of the pilots and
683 ATCOs, which can be used as a mean of identification through speaker identification techniques.
684 Thus, further precautions should be adopted in order to be able to collect this type of data. However,
685 GDPR allow the collection of speech data when made in relation to reasons of substantive public
686 interest, which we found applicable in our case since the project is aimed at enhancing airspace
687 security.

688 9 Conclusions and Future Work

689 This article introduces, the *ATCO2 corpus*, a set of three corpora for research on robust auto-
690 matic speech recognition and natural language understanding of air traffic control communications.
691 In ATCO2, we have successfully created and deployed an operating pipeline for collecting, pre-
692 processing and automatically transcribing ATC audio data. During the data collection period, we
693 mostly relied on a worldwide community of volunteers that acted as 'data feeders'. Then, a community
694 of 'data annotators' employed the SpokenData transcription platform to generate gold annotations
695 of a small portion of the collected data. The platform is up and running, and it is reachable on
696 <https://www.spokendata.com/atco2>.

³²Further information in the following url: <https://www.legislation.gov.uk/ukpga/2006/36/section/48>

³³JO 7210.3CC—Facility Operation and Administration available at https://www.faa.gov/air_traffic/publications/atpubs/foa_html

697 The *ATCO2 corpus* is divided in *ATCO2-PL-set corpus* and *ATCO2-test-set corpus*. The former
698 contains more than 5000 hours of automatically transcribed ATC speech data, spanning more than
699 ten airports in different continents (Table 3). While the latter, *ATCO2-test-set corpus*, contains gold
700 annotations of 4 hours of ATC speech. A subset called *ATCO2-test-set-1h corpus* is offered for free
701 in <https://www.atco2.org/data>. To the authors' knowledge, this is the first public release of a
702 large-scale database for research in the area of air traffic control communications.

703 In addition, we also cover baselines (our source code for data preparation and to replicate the NLU
704 baselines will be stored in the following public GitHub repository [https://github.com/idiap/
705 atco2-corpus](https://github.com/idiap/atco2-corpus).) over three different key tasks in the area of ATC. The first one is related to robust
706 ASR, while the next two are about to NLU of ATC communications.

707 (1) We demonstrated that training an ASR system solely on *ATCO2-PL-set corpus* reaches competitive
708 WERs on both, public and private databases (see Table 5). This is important because *ATCO2-PL-set
709 corpus* is purely composed of pseudo labels generated by ATCO2 project seed ASR system. This
710 can be the starting point for many researchers and companies worldwide that would like to use our
711 corpora for testing and training robust ASR systems for ATC.

712 (2) We demonstrated that as much as 3000 utterances are needed to train and evaluate a BERT-based
713 Named Entity Recognition system for ATC communications. This system is capable of detecting
714 callsigns, commands, and values from the textual inputs. This NLU task is of special interest to the
715 ATC community because this high-level information can be used to assist ATCOs in order to reduce
716 their overall workload.

717 (3) Similarly, we developed a simple yet efficient BERT-based module that performs speaker role
718 detection from textual inputs.

719 Finally, we believe that the 'lessons learned' in ATCO2 project and its recipe for collecting and
720 pre-transcribing large-scale audio databases can be easily transferred to other applications, where
721 data scarcity is a latent problem.

722 Acknowledgements

723 This paper introduces the *ATCO2 Corpus* derived from a joint contribution from Clean Sky 2 Joint
724 Undertaking (JU) and EU-H2020.

725 The work was fully supported by Clean Sky 2 Joint Undertaking (JU) and EU-H2020, under Grant
726 Agreement No. 864702—ATCO2 (Automatic collection and processing of voice data from air-traffic
727 communications).

728 References

- 729 [1] International Civil Aviation Organization, "ICAO phraseology reference guide," 2020.
- 730 [2] Martin Kocour, Karel Veselý, Igor Szöke, Santosh Kesiraju, Juan Zuluaga-Gomez, Alexander
731 Blatt, Amrutha Prasad, Iuliia Nigmatulina, Petr Motlíček, Dietrich Klakow, et al., "Auto-
732 matic processing pipeline for collecting and annotating air-traffic voice communication data,"
733 *Engineering Proceedings*, vol. 13, no. 1, pp. 8, 2021.
- 734 [3] Juan Zuluaga-Gomez, Petr Motlíček, Qingran Zhan, Karel Veselý, and Rudolf Braun, "Au-
735 tomatic Speech Recognition Benchmark for Air-Traffic Communications," in *proceedings of
736 Interspeech 2020*, 2020, pp. 2297–2301.
- 737 [4] Juan Zuluaga-Gomez, Karel Veselý, Alexander Blatt, Petr Motlíček, Dietrich Klakow, Allan
738 Tart, Igor Szöke, Amrutha Prasad, Saeed Sarfjoo, Pavel Kolčárek, et al., "Automatic call
739 sign detection: Matching air surveillance data with air traffic spoken communications," in
740 *Multidisciplinary Digital Publishing Institute Proceedings*, 2020, vol. 59, p. 14.
- 741 [5] José Manuel Cordero, Manuel Dorado, and José Miguel de Pablo, "Automated speech recogni-
742 tion in ATC environment," in *Proceedings of the 2nd International Conference on Application
743 and Theory of Automation in Command and Control Systems*, 2012, pp. 46–53.
- 744 [6] Stephane Pigeon, Wade Shen, Aaron Lawson, and David A van Leeuwen, "Design and
745 characterization of the non-native military air traffic communications database (nnMATC)," in
746 *Eighth Annual Conference of the International Speech Communication Association*, 2007.

- 747 [7] Konrad Hofbauer, Stefan Petrik, and Horst Hering, "The ATCOSIM corpus of non-prompted
748 clean air traffic control speech," in *LREC*, 2008.
- 749 [8] Luboš Šmídl, Jan Švec, Daniel Tihelka, Jindřich Matoušek, Jan Romportl, and Pavel Ircing,
750 "Air traffic control communication (ATCC) speech corpora and their use for ASR and TTS
751 development," *Language Resources and Evaluation*, vol. 53, no. 3, pp. 449–464, 2019.
- 752 [9] John Godfrey, "The Air Traffic Control Corpus (ATC0) - LDC94S14A," 1994.
- 753 [10] J Ferreiros, JM Pardo, R De Córdoba, Javier Macias-Guarasa, JM Montero, F Fernández,
754 Valentin Sama, G González, et al., "A speech interface for air traffic control terminals,"
755 *Aerospace Science and Technology*, vol. 21, no. 1, pp. 7–15, 2012.
- 756 [11] Rosana Ardila, Megan Branson, Kelly Davis, Michael Henretty, Michael Kohler, Josh Meyer,
757 Reuben Morais, Lindsay Saunders, Francis M Tyers, and Gregor Weber, "Common voice: A
758 massively-multilingual speech corpus," *arXiv preprint arXiv:1912.06670*, 2019.
- 759 [12] John J Godfrey, Edward C Holliman, and Jane McDaniel, "SWITCHBOARD: Telephone
760 speech corpus for research and development," in *Acoustics, Speech, and Signal Processing*,
761 *IEEE International Conference on*. IEEE Computer Society, 1992, vol. 1, pp. 517–520.
- 762 [13] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur, "Librispeech: an ASR
763 corpus based on public domain audio books," in *International Conference on Acoustics, Speech*
764 *and Signal Processing (ICASSP)*. IEEE, 2015, pp. 5206–5210.
- 765 [14] Charles T Hemphill, John J Godfrey, and George R Doddington, "The ATIS spoken language
766 systems pilot corpus," in *Speech and Natural Language: Proceedings of a Workshop Held at*
767 *Hidden Valley, Pennsylvania, June 24-27, 1990*, 1990.
- 768 [15] Alice Coucke, Alaa Saade, Adrien Ball, Théodore Bluche, Alexandre Caulier, David Leroy,
769 Clément Doumouro, Thibault Gisselbrecht, Francesco Caltagirone, Thibaut Lavril, et al., "Snips
770 voice platform: an embedded spoken language understanding system for private-by-design
771 voice interfaces," *arXiv preprint arXiv:1805.10190*, 2018.
- 772 [16] Juan Zuluaga-Gomez, Amrutha Prasad, Iuliia Nigmatulina, Saeed Sarfjoo, Petr Motlicek,
773 Matthias Kleinert, Hartmut Helmke, Oliver Ohneiser, and Qingran Zhan, "How Does Pre-
774 trained Wav2Vec2.0 Perform on Domain Shifted ASR? An Extensive Benchmark on Air Traffic
775 Control Communications," *IEEE Spoken Language Technology Workshop (SLT)*, Doha, Qatar,
776 2023.
- 777 [17] Juan Zuluaga-Gomez, Seyyed Saeed Sarfjoo, Amrutha Prasad, Iuliia Nigmatulina, Petr Motlicek,
778 Karel Ondre, Oliver Ohneiser, and Hartmut Helmke, "BERTraffic: BERT-based Joint Speaker
779 Role and Speaker Change Detection for Air Traffic Control Communications," *IEEE Spoken*
780 *Language Technology Workshop (SLT)*, Doha, Qatar, 2023.
- 781 [18] Oliver Ohneiser, Saeed Sarfjoo, Hartmut Helmke, Shruthi Shetty, Petr Motlicek, Matthias
782 Kleinert, Heiko Ehr, and Šarūnas Murauskas, "Robust command recognition for lithuanian air
783 traffic control tower utterances," in *Interspeech*, 2021.
- 784 [19] Bruno Beek, E Neuberg, and David Hodge, "An assessment of the technology of automatic
785 speech recognition for military applications," *IEEE Transactions on Acoustics, Speech, and*
786 *Signal Processing*, vol. 25, no. 4, pp. 310–322, 1977.
- 787 [20] Cheryl J Hamel, David Kotick, and Mark Layton, "Microcomputer system integration for air
788 control training," Tech. Rep., Naval Training Systems Center, Orlando FL, 1989.
- 789 [21] K Matrouf, JL Gauvain, F Neel, and J Mariani, "Adapting probability-transitions in DP matching
790 processing for an oral task-oriented dialogue," in *International Conference on Acoustics, Speech,*
791 *and Signal Processing (ICASSP)*. IEEE, 1990, pp. 569–572.
- 792 [22] Robert Tarakan, Keith Baldwin, and Nicholas Rozen, "An automated simulation pilot capability
793 to support advanced air traffic controller training," in *The 26th Congress of ICAS and 8th AIAA*
794 *ATIO*, 2008.
- 795 [23] Hartmut Helmke, Oliver Ohneiser, Thorsten Mühlhausen, and Matthias Wies, "Reducing
796 controller workload with automatic speech recognition," in *2016 IEEE/AIAA 35th Digital*
797 *Avionics Systems Conference (DASC)*. IEEE, 2016, pp. 1–10.
- 798 [24] Hartmut Helmke, Oliver Ohneiser, Jörg Buxbaum, and Chr Kern, "Increasing ATM effi-
799 ciency with assistant based speech recognition," in *Proc. of the 13th USA/Europe Air Traffic*
800 *Management Research and Development Seminar*, Seattle, USA, 2017.

- [25] Matthias Kleinert, Hartmut Helmke, Shruthi Shetty, Oliver Ohneiser, Heiko Ehr, Amrutha Prasad, Petr Motlicek, and Julia Harfmann, "Automated interpretation of air traffic control communication: The journey from spoken words to a deeper understanding of the meaning," in *2021 IEEE/AIAA 40th Digital Avionics Systems Conference (DASC)*. IEEE, 2021, pp. 1–9.
- [26] Iain McCowan, Jean Carletta, Wessel Kraaij, Simone Ashby, Sebastien Bourban, Mike Flynn, Mael Guillemot, Thomas Hain, Jaroslav Kadlec, Vasilis Karaiskos, et al., "The AMI meeting corpus," in *Proceedings of the 5th international conference on methods and techniques in behavioral research*. Citeseer, 2005, vol. 88, p. 100.
- [27] Anthony Rousseau, Paul Deléglise, and Yannick Esteve, "TED-LIUM: an Automatic Speech Recognition dedicated corpus," in *LREC*, 2012, pp. 125–129.
- [28] Matthias Kleinert, Hartmut Helmke, Gerald Siol, Heiko Ehr, Aneta Cerna, Christian Kern, Dietrich Klakow, Petr Motlicek, Youssef Oualil, Mittul Singh, et al., "Semi-supervised adaptation of assistant based speech recognition models for different approach areas," in *2018 IEEE/AIAA 37th Digital Avionics Systems Conference (DASC)*. IEEE, 2018, pp. 1–10.
- [29] Ajay Srinivasamurthy, Petr Motlicek, Ivan Himawan, Gyorgy Szaszak, Youssef Oualil, and Hartmut Helmke, "Semi-supervised learning with semantic knowledge extraction for improved speech recognition in air traffic control," in *Proc. of the 18th Annual Conference of the International Speech Communication Association*, 2017.
- [30] Estelle Delpech, Marion Laignelet, Christophe Pimm, Céline Raynal, Michal Trzos, Alexandre Arnold, and Dominique Pronto, "A Real-life, French-accented Corpus of Air Traffic Control Communications," in *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*, 2018.
- [31] L Graglia, B Favennec, and A Arnoux, "Vocalise: Assessing the impact of data link technology on the R/T channel," in *24th Digital Avionics Systems Conference*. IEEE, 2005, vol. 1, pp. 5–C.
- [32] Stéphanie Lopez, Anne Condamines, Amélie Josselin-Leray, Mike O'Donoghue, and Rupert Salmon, "Linguistic analysis of english phraseology and plain language in air-ground communication," *Journal of Air Transport Studies*, vol. 4, no. 1, pp. 44–60, 2013.
- [33] JC Segura, T Ehrette, A Potamianos, D Fohr, I Illina, PA Breton, V Clot, R Gemello, M Matasoni, and P Maragos, "The HIWIRE database, a noisy and non-native English speech corpus for cockpit communication," *Online*. <http://www.hiwire.org>, 2007.
- [34] Igor Szöke, Santosh Kesiraju, Ondřej Novotný, Martin Kocour, Karel Veselý, and Jan Černocký, "Detecting English Speech in the Air Traffic Control Voice Communication," in *Proc. Interspeech 2021*, 2021, pp. 3286–3290.
- [35] Hartmut Helmke, Michael Slotty, Michael Poiger, Damián Ferrer Herrero, Oliver Ohneiser, Nathan Vink, Aneta Cerna, Petri Hartikainen, Billy Josefsson, David Langr, et al., "Ontology for transcription of ATC speech commands of SESAR 2020 solution PJ. 16-04," in *IEEE/AIAA 37th Digital Avionics Systems Conference (DASC)*. IEEE, 2018, pp. 1–10.
- [36] Chanwoo Kim and Richard M Stern, "Robust signal-to-noise ratio estimation based on waveform amplitude distribution analysis," in *Ninth Annual Conference of the International Speech Communication Association*, 2008.
- [37] Oldrich Plchot, Pavel Matejka, Ondrej Novotný, Sandro Cumani, Alicia Lozano-Diez, Josef Slavicek, Mireia Diez, Frantisek Grézl, Ondrej Glembek, Mounika Kamsali, et al., "Analysis of BUT-PT Submission for NIST LRE 2017," in *Odyssey*, 2018, pp. 47–53.
- [38] Federico Landini, Ján Profant, Mireia Diez, and Lukáš Burget, "Bayesian HMM clustering of x-vector sequences (VBx) in speaker diarization: theory, implementation and analysis on standard tasks," *Computer Speech & Language*, vol. 71, pp. 101254, 2022.
- [39] Luboš Šmídl, Jan Švec, Daniel Tihelka, Jindřich Matoušek, Jan Romportl, and Pavel Ircing, "Air traffic control communication (ATCC) speech corpora and their use for ASR and TTS development," *Language Resources and Evaluation*, vol. 53, no. 3, pp. 449–464, 2019.
- [40] Thomas Pellegrini, Jérôme Farinas, Estelle Delpech, and François Lancelot, "The Airbus Air Traffic Control speech recognition 2018 challenge: towards ATC automatic transcription and call sign detection," *arXiv preprint arXiv:1810.12614*, 2018.

- [41] Daniel Povey, Arnab Ghoshal, Gilles Boulianne, Lukas Burget, Ondrej Glembek, Nagendra Goel, Mirko Hannemann, Petr Motlicek, Yanmin Qian, Petr Schwarz, et al., “The Kaldi speech recognition toolkit,” in *IEEE workshop on automatic speech recognition and understanding*. IEEE Signal Processing Society, 2011, number CONF.
- [42] Nelson Morgan, Herve Boulard, Steve Renals, Michael Cohen, and Horacio Franco, “Hybrid neural network/hidden markov model systems for continuous speech recognition,” in *Advances in Pattern Recognition Systems Using Neural Network Technologies*, pp. 255–272. World Scientific, 1993.
- [43] Herve A Boulard and Nelson Morgan, *Connectionist speech recognition: a hybrid approach*, vol. 247, Springer Science & Business Media, 1993.
- [44] George Saon, Hagen Soltau, David Nahamoo, and Michael Picheny, “Speaker adaptation of neural network acoustic models using i-vectors,” in *2013 IEEE Workshop on Automatic Speech Recognition and Understanding*. IEEE, 2013, pp. 55–59.
- [45] Daniel Povey, Vijayaditya Peddinti, Daniel Galvez, Pegah Ghahremani, Vimal Manohar, Xingyu Na, Yiming Wang, and Sanjeev Khudanpur, “Purely Sequence-Trained Neural Networks for ASR Based on Lattice-Free MMI,” in *INTERSPEECH 2016, San Francisco, CA, USA, September 2016*. 2016, pp. 2751–2755, ISCA.
- [46] Daniel Povey, Gaofeng Cheng, Yiming Wang, Ke Li, Hainan Xu, Mahsa Yarmohammadi, and Sanjeev Khudanpur, “Semi-orthogonal low-rank matrix factorization for Deep Neural Networks,” in *Proceedings of INTERSPEECH 2018*, 09 2018, pp. 3743–3747.
- [47] Juan Zuluaga-Gomez, Iuliia Nigmatulina, Amrutha Prasad, Petr Motlicek, Karel Veselý, Martin Kocour, and Igor Szöke, “Contextual Semi-Supervised Learning: An Approach to Leverage Air-Surveillance and Untranscribed ATC Data in ASR Systems,” in *Interspeech*, 2021, pp. 3296–3300.
- [48] Martin Kocour, Karel Veselý, Alexander Blatt, Juan Zuluaga Gomez, Igor Szöke, Jan Cernocky, Dietrich Klakow, and Petr Motlicek, “Boosting of Contextual Information in ASR for Air-Traffic Call-Sign Recognition,” in *Interspeech*, 2021, pp. 3301–3305.
- [49] Iuliia Nigmatulina, Juan Zuluaga-Gomez, Amrutha Prasad, Seyyed Saeed Sarfjoo, and Petr Motlicek, “A two-step approach to leverage contextual data: speech recognition in air-traffic communications,” in *ICASSP*, 2022.
- [50] Iuliia Nigmatulina, Rudolf Braun, Juan Zuluaga-Gomez, and Petr Motlicek, “Improving callsign recognition with air-surveillance data in air-traffic communication,” *arXiv preprint arXiv:2108.12156*, 2021.
- [51] Yi Lin, “Spoken instruction understanding in air traffic control: Challenge, technique, and application,” *Aerospace*, vol. 8, no. 3, pp. 65, 2021.
- [52] Amrutha Prasad, Juan Zuluaga-Gomez, Petr Motlicek, Oliver Ohneiser, Hartmut Helmke, Saeed Sarfjoo, and Iuliia Nigmatulina, “Grammar Based Identification Of Speaker Role For Improving ATCO And Pilot ASR,” *arXiv preprint arXiv:2108.12175*, 2021.
- [53] Hartmut Helmke, Matthias Kleinert, Shruthi Shetty, Oliver Ohneiser, Heiko Ehr, Hörður Arilússon, Teodor S Simiganoschi, Amrutha Prasad, Petr Motlicek, Karel Veselý, et al., “Readback error detection by automatic speech recognition to increase ATM safety,” in *Proceedings of the Fourteenth USA/Europe Air Traffic Management Research and Development Seminar (ATM2021), Virtual Event*, 2021, pp. 20–23.
- [54] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova, “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding,” *arXiv preprint arXiv:1810.04805*, 2018.
- [55] Sowmya Vajjala and Ramya Balasubramaniam, “What do we Really Know about State of the Art NER?,” *arXiv preprint arXiv:2205.00034*, 2022.
- [56] Ralph Grishman and Beth M Sundheim, “Message understanding conference-6: A brief history,” in *COLING 1996 Volume 1: The 16th International Conference on Computational Linguistics*, 1996.
- [57] Ronan Collobert, Jason Weston, Léon Bottou, Michael Karlen, Koray Kavukcuoglu, and Pavel Kuksa, “Natural language processing (almost) from scratch,” *Journal of machine learning research*, vol. 12, pp. 2493–2537, 2011.

- [58] Jakub Piskorski, Lidia Pivovarov, Jan Šnajder, Josef Steinberger, and Roman Yangarber, “The first cross-lingual challenge on recognition, normalization, and matching of named entities in Slavic languages,” in *Proceedings of the 6th Workshop on Balto-Slavic Natural Language Processing*, 2017, pp. 76–85.
- [59] Vikas Yadav and Steven Bethard, “A survey on recent advances in named entity recognition from deep learning models,” in *Proceedings of the 27th International Conference on Computational Linguistics*, 2018, pp. 2145–2158.
- [60] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov, “RoBERTa: A Robustly Optimized BERT Pretraining Approach,” *arXiv preprint arXiv:1907.11692*, 2019.
- [61] Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen, “DeBERTa: Decoding-enhanced BERT with Disentangled Attention,” in *International Conference on Learning Representations*, 2021.
- [62] Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf, “DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter,” *arXiv preprint arXiv:1910.01108*, 2019.
- [63] Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, et al., “Transformers: State-of-the-art natural language processing,” in *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, 2020, pp. 38–45.
- [64] Quentin Lhoest, Albert Villanova del Moral, Yacine Jernite, Abhishek Thakur, Patrick von Platen, Suraj Patil, Julien Chaumond, Mariama Drame, Julien Plu, Lewis Tunstall, et al., “Datasets: A community library for natural language processing,” in *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, 2021, pp. 175–184.
- [65] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov, “Dropout: a simple way to prevent neural networks from overfitting,” *The journal of machine learning research*, vol. 15, no. 1, pp. 1929–1958, 2014.
- [66] Dan Hendrycks and Kevin Gimpel, “Gaussian error linear units (gelus),” *arXiv preprint arXiv:1606.08415*, 2016.
- [67] Razvan Pascanu, Tomas Mikolov, and Yoshua Bengio, “On the difficulty of training recurrent neural networks,” in *International conference on machine learning*. PMLR, 2013, pp. 1310–1318.
- [68] Ilya Loshchilov and Frank Hutter, “Decoupled weight decay regularization,” in *International Conference on Learning Representations*, 2019.
- [69] Alexander Blatt, Martin Kocour, Karel Veselý, Igor Szöke, and Dietrich Klakow, “Call-sign recognition and understanding for noisy air-traffic transcripts using surveillance information,” in *ICASSP*, 2022, pp. 8357–8361.
- [70] Zhiyong He, Zanbo Wang, Wei Wei, Shanshan Feng, Xianling Mao, and Sheng Jiang, “A Survey on Recent Advances in Sequence Labeling from Deep Learning Models,” *arXiv preprint arXiv:2011.06727*, 2020.
- [71] Cheng Zhou, Boris Cule, and Bart Goethals, “Pattern based sequence classification,” *IEEE Transactions on knowledge and Data Engineering*, vol. 28, no. 5, pp. 1285–1298, 2015.
- [72] Tilak Purohit, Imen Ben Mahmoud, Bogdan Vlasenko, and Mathew Magimai Doss, “Comparing supervised and self-supervised embedding for ExVo Multi-Task learning track,” *arXiv preprint arXiv:2206.11968*, 2022.
- [73] Marouane Birjali, Mohammed Kasri, and Abderrahim Beni-Hssane, “A comprehensive survey on sentiment analysis: Approaches, challenges and trends,” *Knowledge-Based Systems*, vol. 226, pp. 107134, 2021.
- [74] Mickaël Rigault, Claudia Cevenini, Khalid Choukri, Martin Kocour, Karel Veselý, Igor Szöke, Petr Motlicek, Juan Pablo Zuluaga-Gomez, et al., “Legal and ethical challenges in recording air traffic control speech,” in *Proceedings of the Workshop on Ethical and Legal Issues in Human Language Technologies and Multilingual De-Identification of Sensitive Data In Language Resources within the 13th Language Resources and Evaluation Conference*, 2022, pp. 79–83.

A Automatic Transcription Engine

This annex describes in details how we collected the audio and metadata that brought to live the *ATCO2 corpus*. We mainly rely on the automatic transcription engine, described in more details in Section 4.3. The automatic transcription engine is implemented as a scalable cloud service. It communicates with other services (or partners) using APIs. This service is designed to process large flows of data produced by data feeders.³⁴

The data is pushed to this service by OSN³⁵ servers by calling an API request and providing a job setting JSON file. After the request is accepted, settings parameters are processed and the job is stored in an internal queue for processing. The user (in this case, OSN) may have an ability to tweak the settings and to affect the processing pipeline and the result. Namely:

- Audio input format choices;
- Rejection threshold for too long audios;
- Rejection threshold for too short audios;
- Rejection threshold for too noisy audios;
- Rejection threshold for non-English audios;
- Switching the language of automatic speech recognizer.

Most of these are actually disabled due to security reasons (not to interrupt the processing pipeline), but may be easily enabled on the fly if needed. The overall data flow model is described in Figure 9. Any new job (request for a full automatic annotation of recording) accepted via API on the SpokenData³⁶ side is processed by a master processing node. The job is enqueued into a workload manager queue. Once there is a free processing slot, the job is submitted to a processing server, or worker. The master processing node then informs the OSN server about the state of the job by calling a callback.

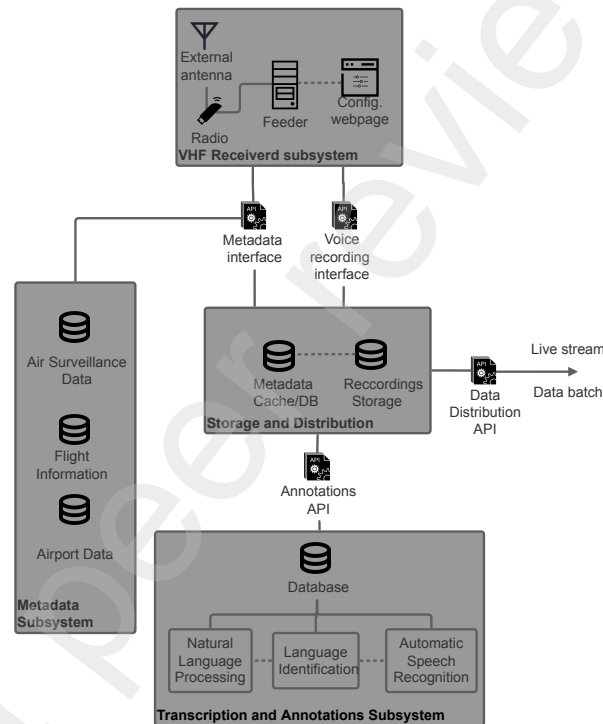


Figure 9: Overall ATCO2 communication schema.

³⁴Enthusiasts that act as 'feeders' of ATC speech and contextual ATC data (surveillance). See Section 4.1.

³⁵OpenSky Network: <https://opensky-network.org/>.

³⁶Industrial partner: <https://www.spokendata.com/atco2>.

1000 B Full processing pipeline

1001 The processing pipeline is implemented as a Python script which follows a configuration file, i.e.,
 1002 `worker.py`. The configuration file allows us to modify the logic and flow of the data in the pipeline
 1003 on the fly. It allows parallelism, forking, and conditions. In principle, `worker.py` consists of global
 1004 definitions (constants), blocks (local definitions) and links (an acyclic oriented graph) between blocks.
 1005 The processing pipeline is given on Figure 10. For instance, we address in previous work [2, 4]
 1006 early implementations of each technology, e.g., segmentation and diarization, ASR or named entity
 1007 recognition. All the technologies and tools are encapsulated in a BASH scripts with a unified interface.

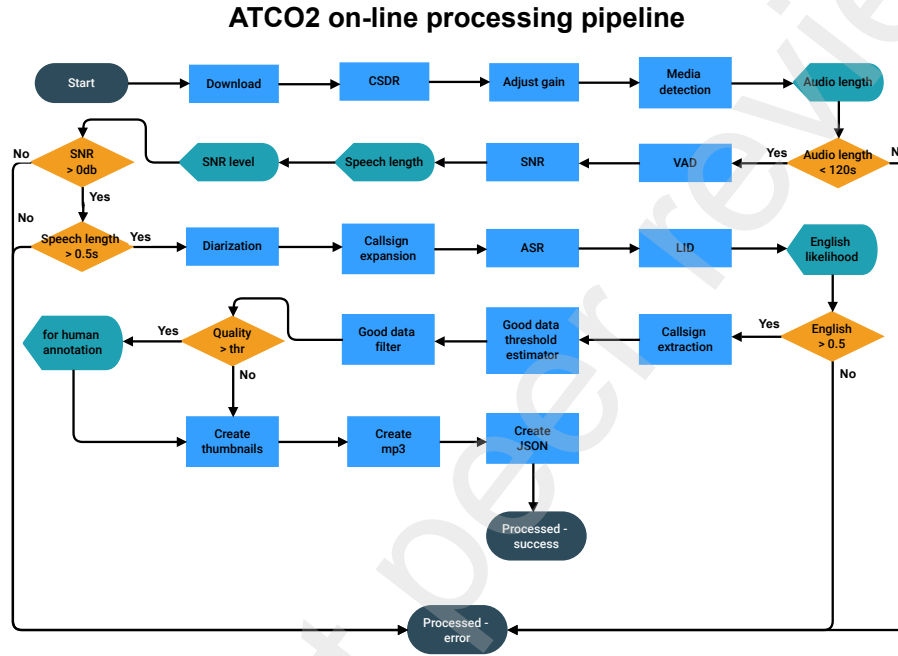


Figure 10: Diagram of the processing pipeline. The blue rectangles are processes. The cyan arrow blocks are internal callback events, where the pipeline informs the master node about progress and sends intermediate results. Finally, the orange rhombuses are conditions. Here the intermediate results are taken (e.g., an SNR level) and it is decided if it makes sense to continue (clean audio) or stop processing, e.g., a given segment reached the maximum allowed noise level. A final internal callback is run when the pipeline finishes. It triggers the API to call the OSN server with the particular callback (processing done as *OK* or *ERROR*).

1008 The first row of blocks from Figure 10 refers to segmentation and demodulation. First, an antenna,
 1009 and a recording device jointly capture the radio signal, which is divided into segments containing
 1010 portions where the transmission was “active”, the silent parts are not recorded (push-to-talk is used
 1011 in ATC voice communication). This functionality is part of the RTLSDR-Airband audio recording
 1012 software, from which we dump the raw I/Q signal. Second, we convert this complex I/Q radio signal
 1013 into a waveform signal by a software defined radio CSDR. The first part is done in the recording
 1014 device, while the second is done at OpenSky Network servers. Next, we do “signal-to-noise ratio
 1015 (SNR) filtering” (second row), the purpose is to remove the recordings that are too noisy. In bad
 1016 recording conditions, we can end up in a situation in which the voice is not intelligible. The following
 1017 step is “diarization” (third row). In the automatically segmented data, some recordings contain more
 1018 than one speaker. This is a problem, because we intend to automatically transcribe speaker turns of
 1019 single speakers. And, for subsequent NLP/SLU tasks, it is important to separate the speaker turns
 1020 as well. The diarization solves this by splitting the audio into segments with single-speakers and
 1021 assigning them speaker labels. In the ASR step, we simply convert “speech-to-text”. This is done
 1022 by our ASR system that we build with tools from the Kaldi toolkit [41]. The output from this step
 1023 are transcripts which, inevitably, contain some errors. To improve the accuracy of the transcripts,

1024 we use contextual information (call-sign lists from surveillance data). The mechanism is that we
1025 give score discounts to some rare ‘words’ in the lattice-generation step, or we give score discounts to
1026 some ‘word sequences’ by rescoreing lattices of alternative hypotheses (further details in [48, 50]. The
1027 call-sign lists come from the traffic monitoring databases of OpenSky Network. Next, the transcripts
1028 are used as an input for the English language detection (ELD) system. The purpose is to be able to
1029 discard non-English audio data. The typical state-of-the-art language identification system is based
1030 on acoustic modeling, and uses audio as input. However, for the ATC speech, we don’t need to
1031 “identify” the non-English language, so we developed a “lexical English detection system” which
1032 uses transcripts and confidence scores produced by ASR as its inputs. For ATC speech, this worked
1033 better than the “traditional” acoustic language identification method. The last automatic operation is
1034 “post-processing by NLP”. Currently, we have a Callsign-code Extractor that returns the callsign in
1035 ICAO format like “DLH77RM” belonging to an aircraft. Finally, some processed data go through
1036 “human correction”, and some data are kept with the automatic labels. The former case produced
1037 *ATCO2-test-set corpus*, while the latter, *ATCO2-PL-set corpus*.

This annex conveys our main results of transcripts unification and lexicon formatting. Note that the description below is related to the databases employed to train the seed ASR engine used during the pre-transcription process, described in Section 4.3. Special attention was devoted to the unification of words from the radiotelephony alphabet and numbers (see *ICAO alphabet* column from Table 8). Note that we map the word 'niner' → 'nine', and in the pronunciation lexicon, we allow the word 'nine' to be pronounced as 'n ay1 n er0' (phoneme-based format). Also, some standard expressions can be written as two words or as a single word. For some of the frequent ones, we selected one version that is used systematically (see *Common expressions* column from Table 8). We also rectify some airline designators that are part of the callsigns uttered by the ATCOs and pilots (see *Airline designators* column from Table 8).

We derive a table of mapping rules by extracting insights from a diverse list of airline designators. In total, we have a list of 5.4k airline designators, out of these, there are 1.8k multi-word airline designators. The airline designators ligatured by underscore are easier to be produced by the 'speech-to-text' system as the tokens are longer, and there is also less uncertainty to be modelled by the language model. Finally, we pay extra attention to the transcripts generated by the ATCO2 community of volunteers. Like in any other human input, there might be typos or other types of transcription errors. It is necessary to at least revise the transcripts by the 2nd round of human inspection, where the errors are ideally fixed.

Table 8: Normalization rules applied for annotation.

Unification of transcripts		
ICAO alphabet	Common expressions	Airline designators
alpha → alfa	take off → takeoff	qatar → qatari
charly → charlie	call sign → callsign	turkey → turkish
juliet → juliett	readback → read back	air france → airfrans
oskar → oscar	flightlevel → flight level	norshuttle → nor shuttle
xray → x-ray	stand by → standby	airvan → air van
zoulou → zulu	start up → startup	rynair → ryanair
whisky → whiskey	goodbye → good bye	airbaltic → air_baltic
tripple → triple	clear for → cleared for	air berlin → air_berlin
niner → nine	lineup → line up	air canada → air_canada
0 → zero	clear for → cleared for	air china → air_china
1 → one	turnright → turn right	air europe → air_europe
2 → two	oclock → o'clock	jet stream → jet_stream
3 → three	o clock → o'clock	jetstream → jet_stream
4 → four	push back → pushback	k l m → k_l_m
5 → five	descent direct → descend direct	klm → k_l_m
6 → six	goodbye → good bye	korean air → korean_air
7 → seven	goodday → good day	koreanair → korean_air
8 → eight	turbulence → turbulence	wizzair → wizz_air
9 → nine	til → till	top_jet → topjet

1057 D How a Sample From ATCO2 corpora Looks Like?

1058 Example of human annotations for a recording of *ATCO2-test-set corpus* in XML format. This file
1059 encodes most of the metadata. If more than one segment is present, it means there are two or more in
1060 the recording:

```
1061 1 <?xml version="1.0" encoding="utf-8"?>
1062 2 <data>
1063 3     <segment>
1064 4         <start>0</start>
1065 5         <end>2.93</end>
1066 6         <speaker>B</speaker>
1067 7         <speaker_label>pilot</speaker_label>
1068 8         <text>[unk] [#callsign]Quebec Lima[/#callsign] [#
1069 command]confirm cleared for ILS[/#command] [unk]</text>
1070 9         <tags>
107110             <correct>0</correct>
107211             <correct_transcript>1</correct_transcript>
107312             <correct_tagging>0</correct_tagging>
107413             <non_english>0</non_english>
107514         </tags>
107615     </segment>
107716     <segment>
107817         <start>2.99</start>
107918         <end>10.45</end>
108019         <speaker>A</speaker>
108120         <speaker_label>ATCO approach</speaker_label>
108221         <text>[unk] [#callsign]Quebec Lima[/#callsign] [#
1083 command]affirm cleared ILS approach[/#command] [#value]runway one
1084 four[/#value] [#command]if you go around[/#command] [#value]runway
1085 one four[/#value] [#command]report in localizer established[/#
1086 command]</text>
108722         <tags>
108823             <correct>0</correct>
108924             <correct_transcript>1</correct_transcript>
109025             <correct_tagging>0</correct_tagging>
109126             <non_english>0</non_english>
109227         </tags>
109328     </segment>
109429 </data>
```

Listing 1: XML tagged example from *ATCO2-test-set corpus*. This example contains two recordings separated by the `<segment>` tag.

1095 Basic details from the previous XML tagged segment:

- 1096 • `<segment> ... </segment>`: one sample of data. One recording may have one or more
1097 segments;
- 1098 • `<start> ... </end>`: timing information with speech activity by the speakers;
- 1099 • `<speaker> ... </speaker>`: speaker information to identify whether the segment is from an
1100 ATCO or pilot. Unknown cases are tagged with `<UNK>`
- 1101 • `<text> ... </text>`: ground truth transcripts with high-level entities annotations (callsigns,
1102 commands and values). Not all the segments contains these annotations.
- 1103 • `<tags> ... </tags>`: extra metadata.