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Introduction to Music Processing

Neural Models

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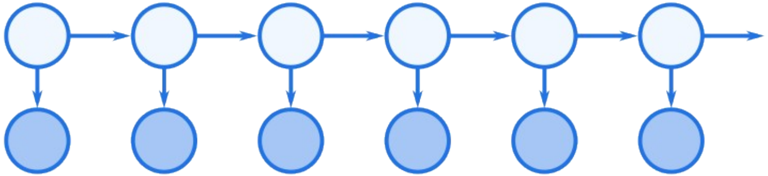
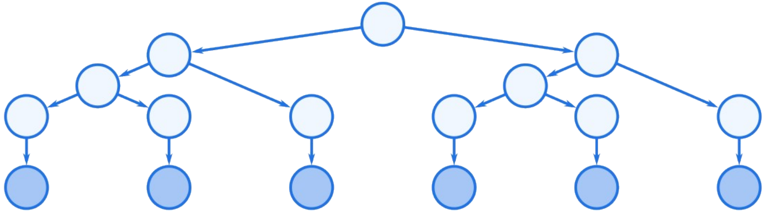
Computational Models of Music

- **Sequential Models** (*n*-gram and (hidden) Markov)



- **Hierarchical Models** (context-free grammars)



- **Neural Networks** (RNNs, Transformers, WaveNet)

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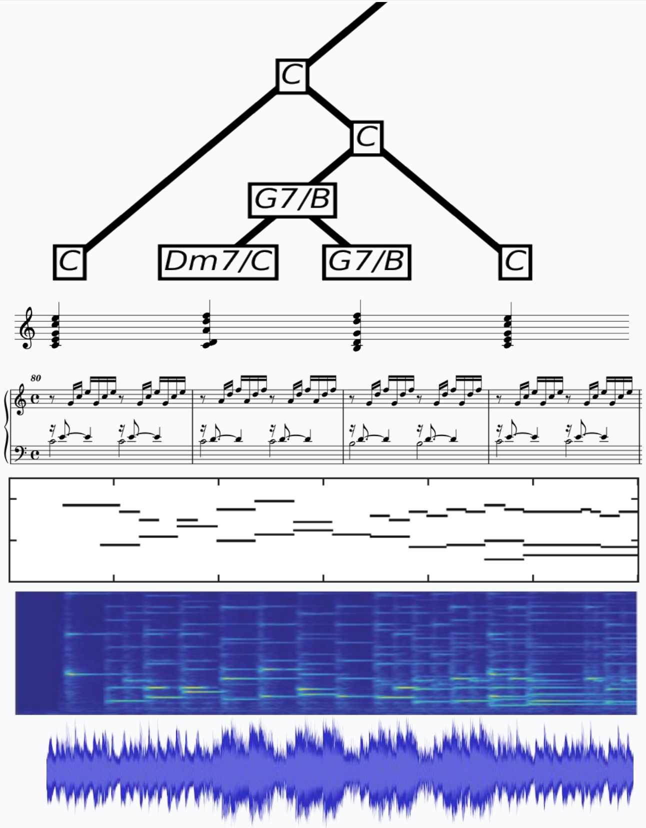
Neural Networks

for Music Analysis and Generation

Music Representations

Analysis



Structure Analysis

Chords/Harmonies

Score

Pianoroll/MIDI

Spectrogram

Waveform/Audio

Benetos et al. (2019) / Lieck & Rohrmeier (2021)

Generation

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Combining Multiple Architectures & Representations

- **Source representation(s):** The representation(s) of the input data
- **Target representation:** The representation of the desired output
- **Intermediate/Auxiliary representation(s):** Any representation(s) used in intermediate or additional processing steps

Examples

- **Raw audio generation:** (audio) → (MIDI / tokens) → audio
- **Transcription:** audio → (spectrogram) → MIDI → score → (audio)
- **Chord analysis:** score → chords
- **Metrical analysis:** audio → onsets → beat → metre

Note: Encoder-decoder architectures combine analysis and generation!

Generative Audio Models ("best of big tech")

These models combine multiple architectures & representations:

- MusicGen (Meta): https://ai.honu.io/papers/musicgen/
  Copet J, Kreuk F, Gat I, et al (2024) Simple and controllable music generation. In: Advances in Neural Information Processing Systems
- MusicLM (Google): https://google-research.github.io/seanet/musiclm/examples/
  Agostinelli A, Denk TI, Borsos Z, et al (2023) MusicLM: Generating Music From Text http://arxiv.org/abs/2301.11325
- Jukebox (OpenAI): https://openai.com/research/jukebox | https://jukebox.openai.com/
  Dhariwal P, Jun H, Payne C, et al (2020) Jukebox: A Generative Model for Music http://arxiv.org/abs/2005.00341
- MuseNet (OpenAI): https://openai.com/research/musenet
  (2019)
- Music Transformer (Google): https://magenta.tensorflow.org/music-transformer
  Huang C-ZA, Vaswani A, Uszkoreit J, et al (2018) Music Transformer: Generating Music with Long-Term Structure

Generative Audio Models (“best of big tech”)

Common Strengths…

- Getting the “feel” right (high-level surface features of genres etc.)
- Basic musical structure (e.g. isochronous beat, “keyness”, surface texture)
- Decent short-term *structure* (range of seconds)
- Decent long-term *coherence* (e.g. staying in style/key)

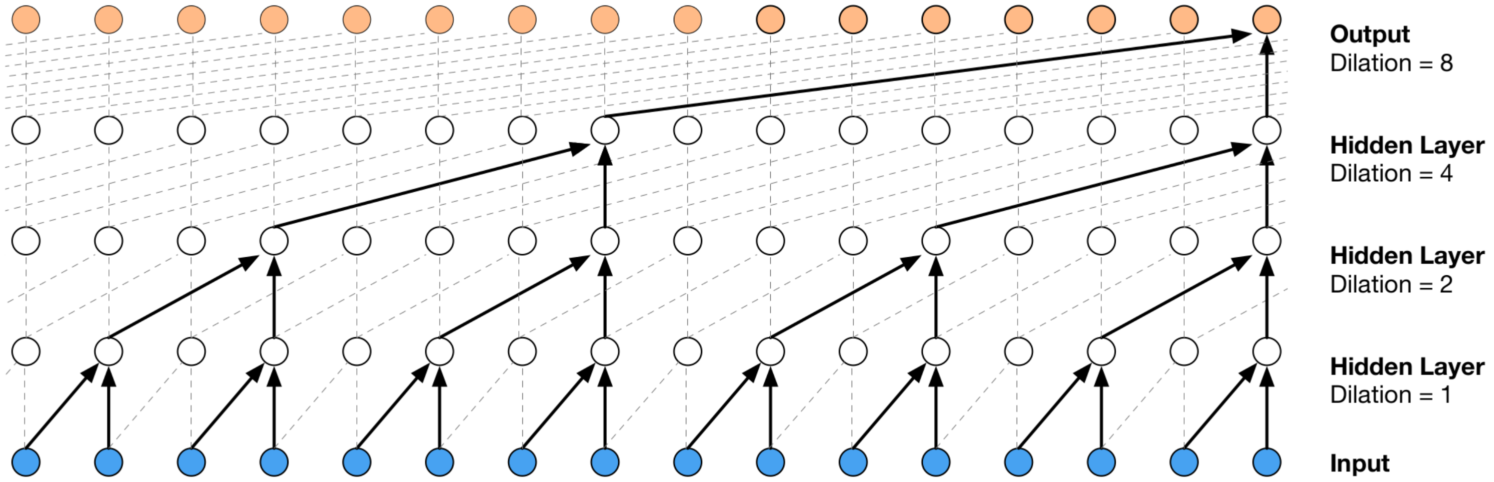
…and Shortcomings…

- Mediocre audio quality (esp. given the amount of training data)
  → This has changed in more recent models!
- Inaccurate details in all musical dimensions (timing, pitch, harmony, …)
- **No long-term structure** (range of minutes or more)

WaveNet: (conditional) → audio

Raw autoregressive audio generation (optionally conditional)

- Uses *dilated causal convolutional layers* (with residual and skip connections)
- μ-law companding algorithm to *discretise* to 256 prediction values (nowadays VQ approaches are commonly used)



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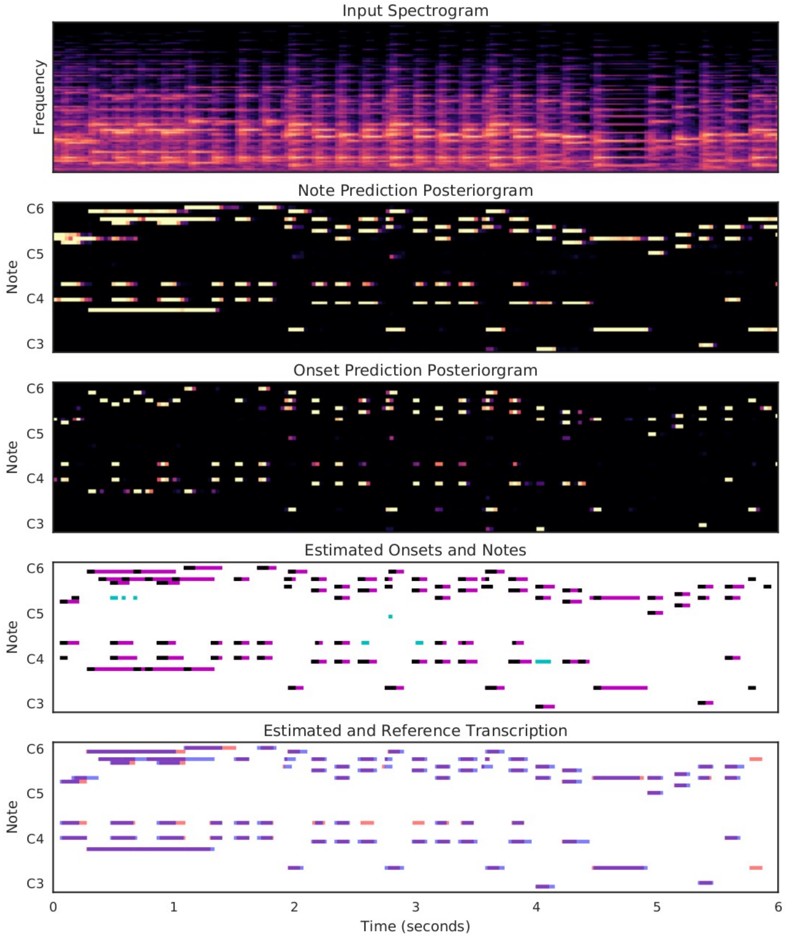
van den Oord A, Dieleman S, Zen H, et al (**2016**) WaveNet: A generative model for raw audio. arXiv preprint arXiv:160903499

Onset and Frames: audio → MIDI

Predict MIDI from raw audio

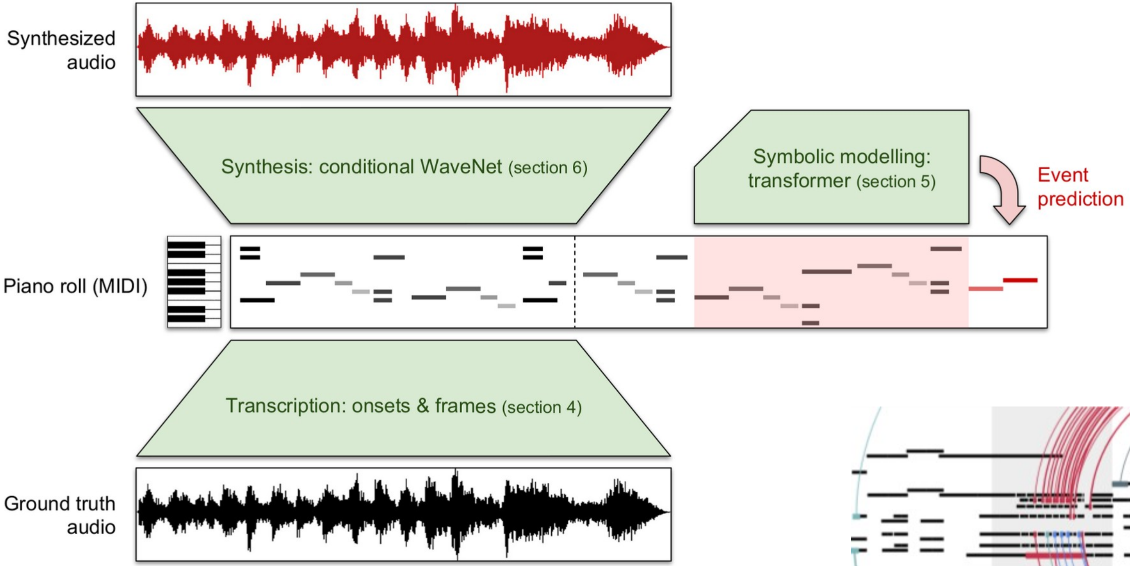
- Estimate notes (pitches)
- Estimate (note-wise) onsets
- Predict notes that also have an onset

Hawthorne C, Elsen E, Song J, et al (2018) Onsets and Frames: Dual-Objective Piano Transcription. In: Proceedings of the 19th International Society for Music Information Retrieval Conference



Music Transformer

- Autoregressive symbolic generation
- audio → symbolic → audio (Wave2Midi2Wave)



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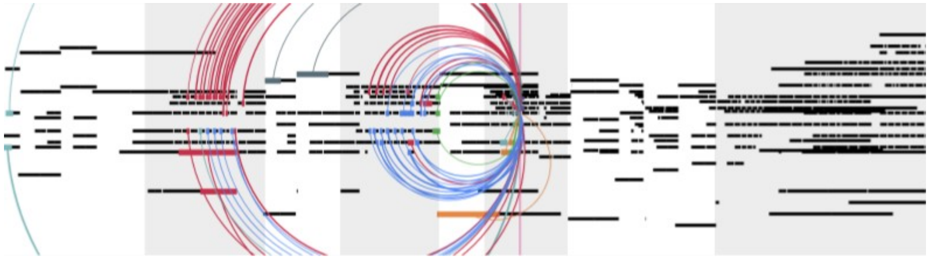

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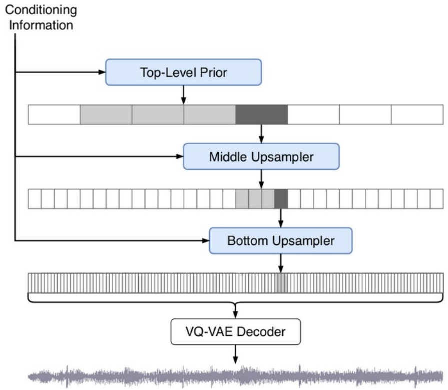
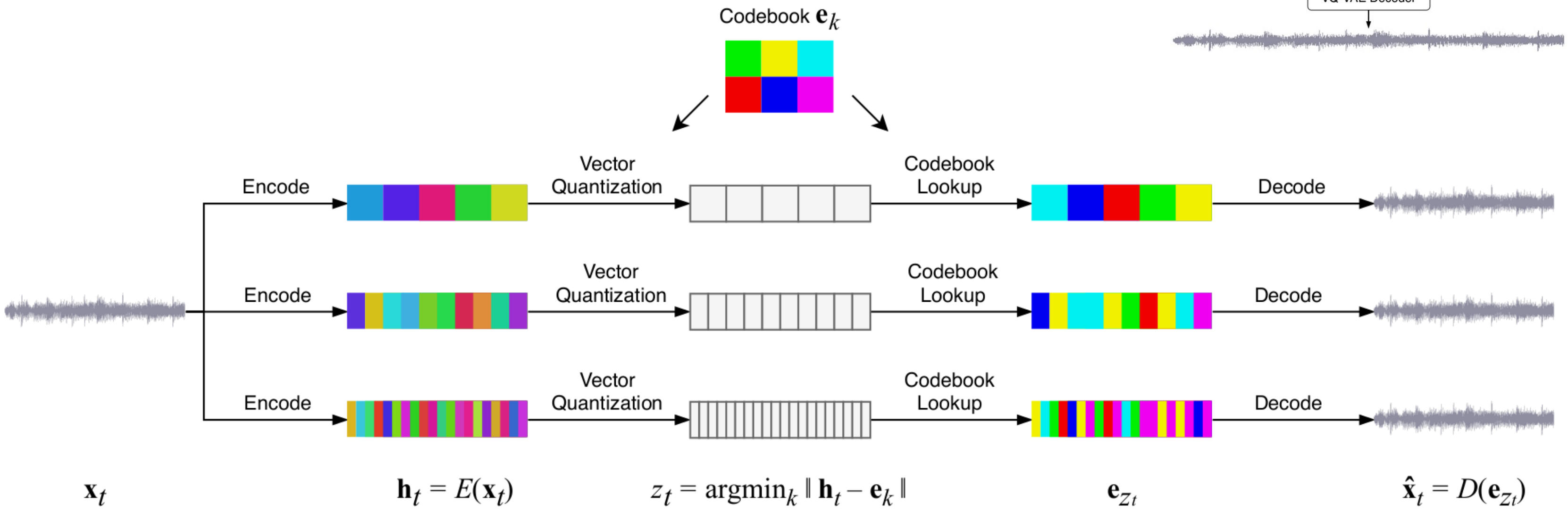
Jukebox

- audio → discrete latent (VQ-VAE) → audio
- three separate time scales
- transformer in latent space





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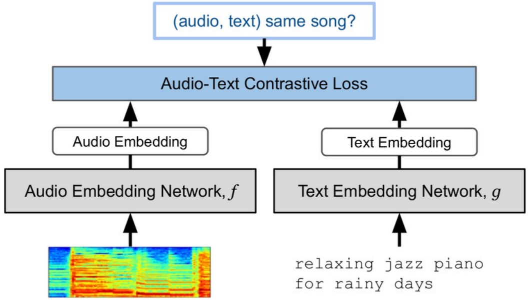
Dhariwal P, Jun H, Payne C, et al (2020) Jukebox: A Generative Model for Music http://arxiv.org/abs/2005.00341

MusicLM

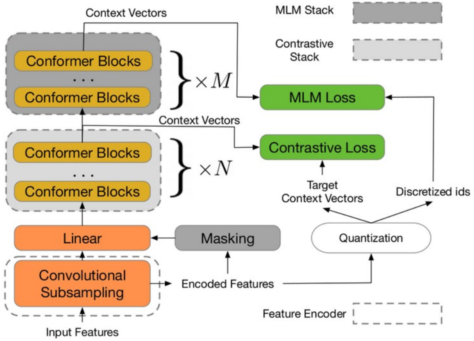
MuLan

- Joint audio-text embedding
- → relate text to audio



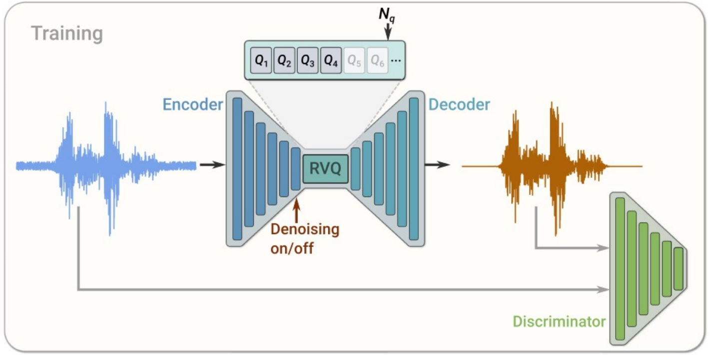
w2v-BERT

- Semantic audio tokens
- Masked contrastive loss
- → learn "meaning" of audio



SoundStream

- Discrete neural audio codec
- → capture waveform of audio



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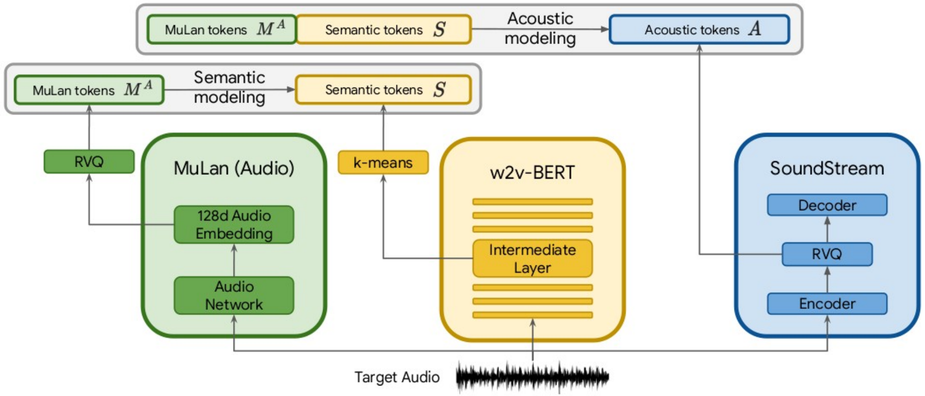
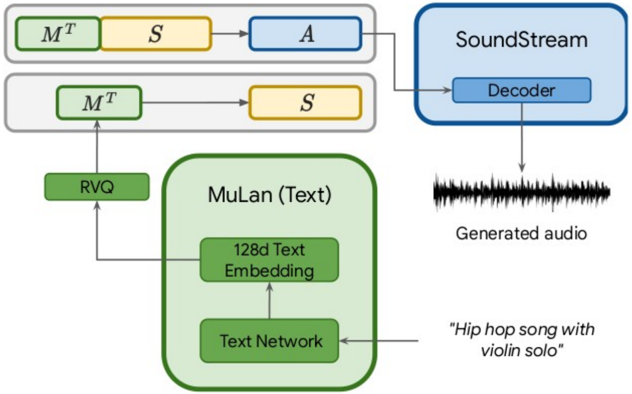
MusicLM

Combine three modules

1) Get embedding from audio (training) or text (inference)
2) Generate semantic audio tokens from embedding
3) Generate audio codes from embedding and tokens

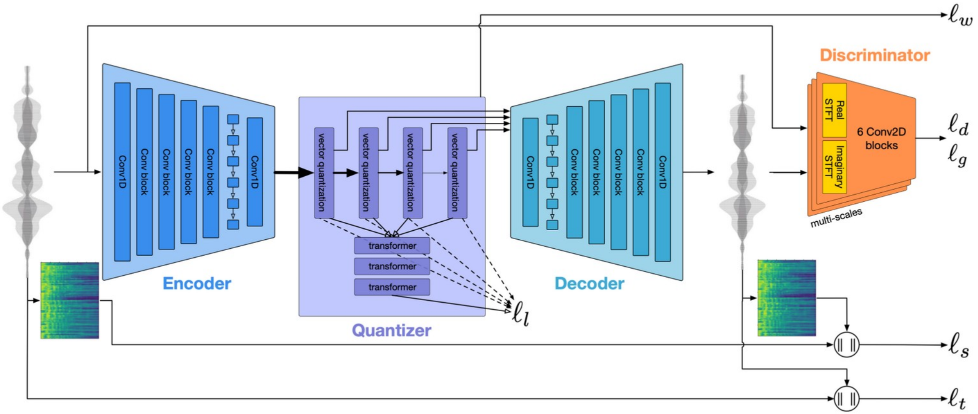


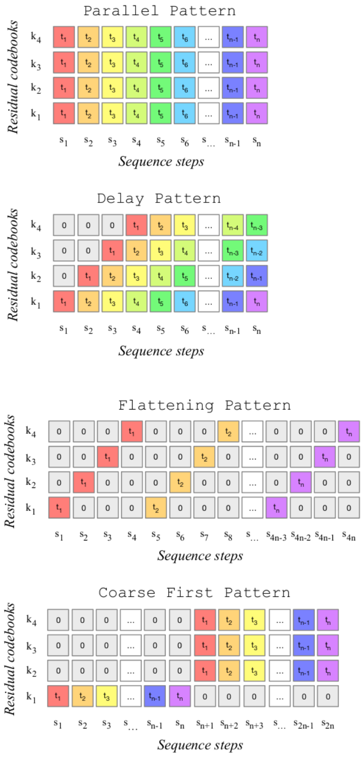


Agostinelli A, Denk TI, Borsos Z, et al (2023) MusicLM: Generating Music From Text http://arxiv.org/abs/2301.11325

MusicGen

- Encode to discrete tokens (multiple residual streams)
  - time and frequency (mel-spectrogram) reconstruction loss
  - discriminative STFT loss
- Model sequence of discrete tokens using transformer





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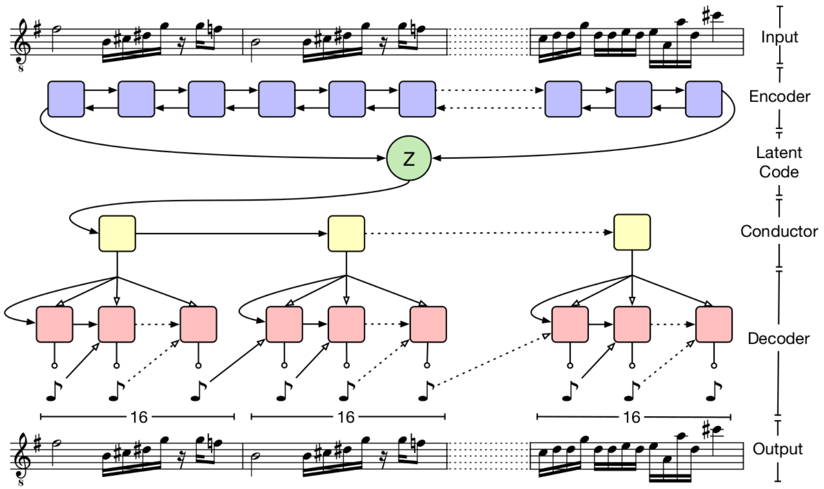
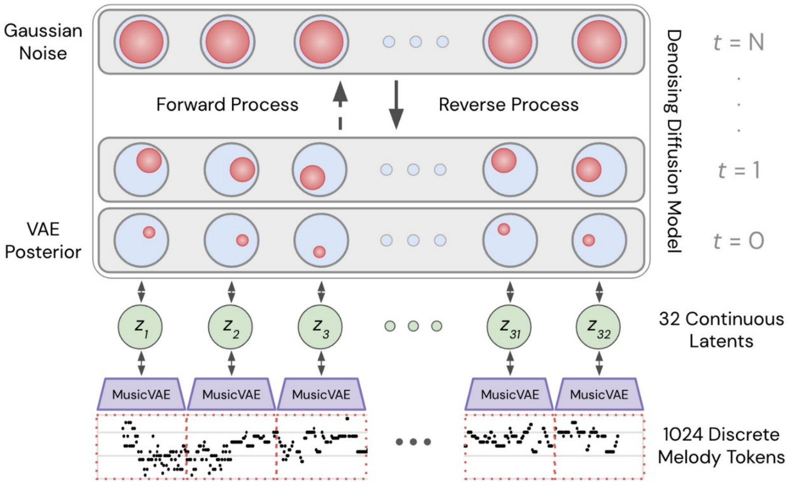
Symbolic Generation with Diffusion Models

- MIDI → continuous latent (VAE) → MIDI
- continuous latent (diffusion) → MIDI

MusicVAE





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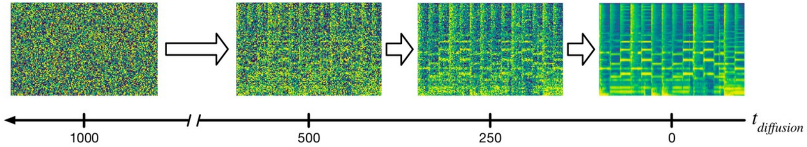
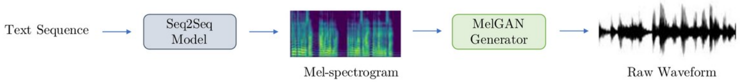
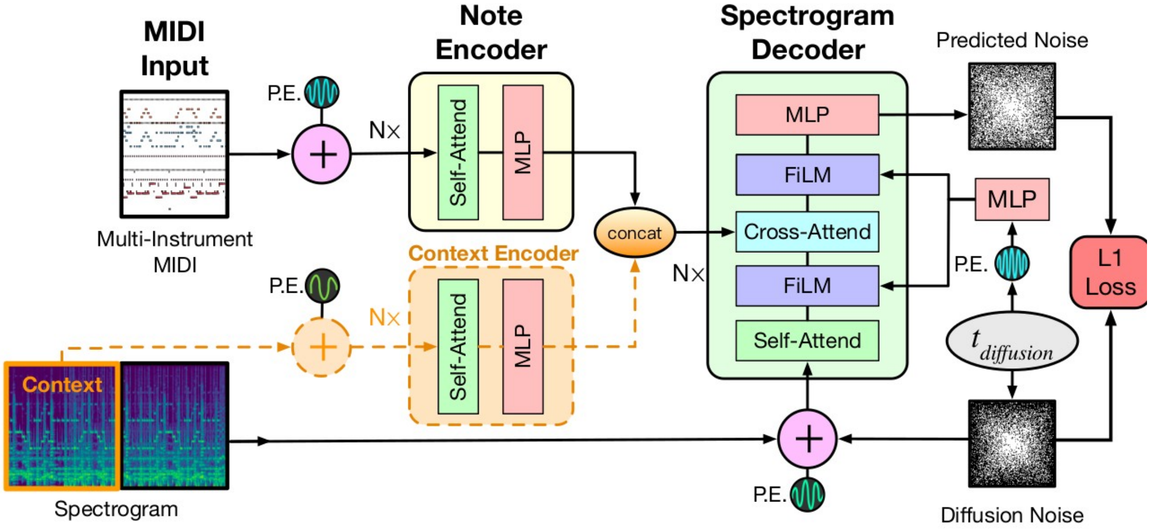
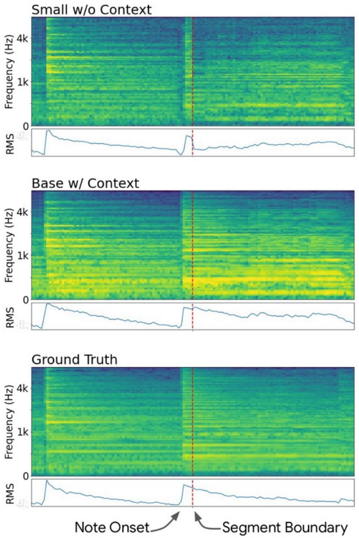
Spectrogram/Audio Generation with Diffusion Models









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- Kumar K, Kumar R, de Boissiere T, et al (2019) Melgan: Generative adversarial networks for conditional waveform synthesis. Advances in neural information processing systems

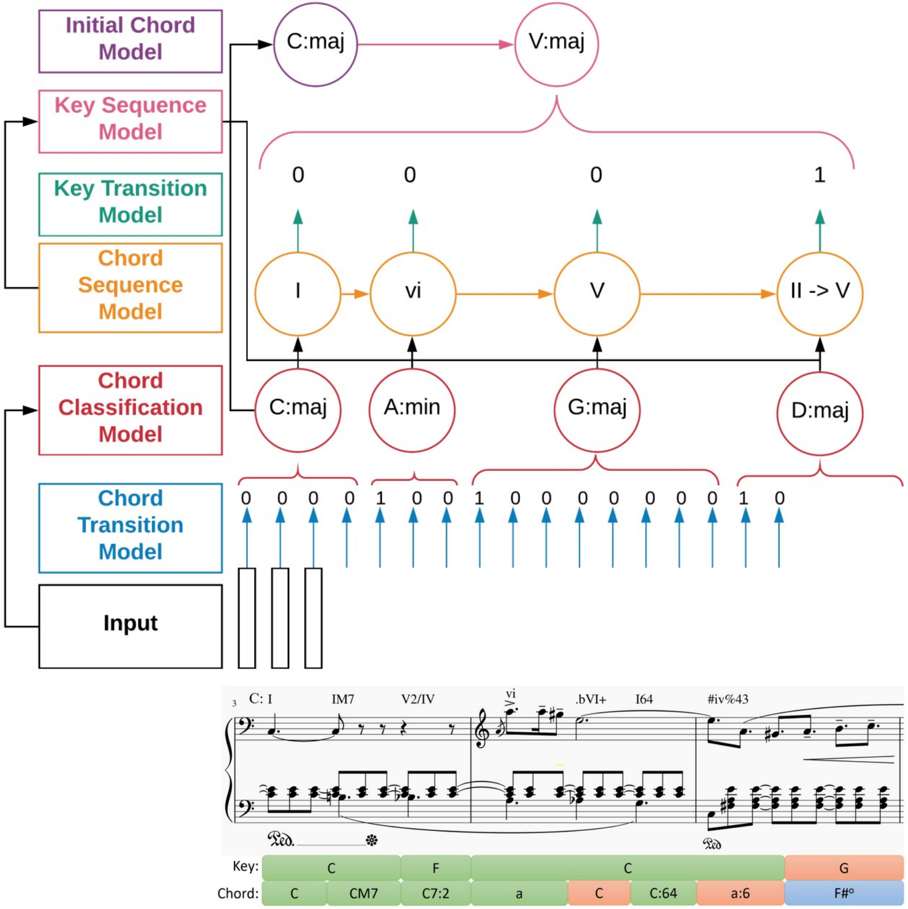
Harmonic Analysis

Vocabulary (1540 possible chords)

- 35 root pitches (A♭♭ – G♯♯), 70 keys (major/minor)
- 12 chord types
  - major, minor, augmented (triad, major 7th, minor 7th)
  - diminished (triad, minor 7th, diminished 7th)
- 3 or 4 inversions (triads/tetrads)

Architecture

- Modular with well-defined outputs
- Note features as one-hot vectors
- Bi-LSTM for sequence modules
- Using beam search for inference



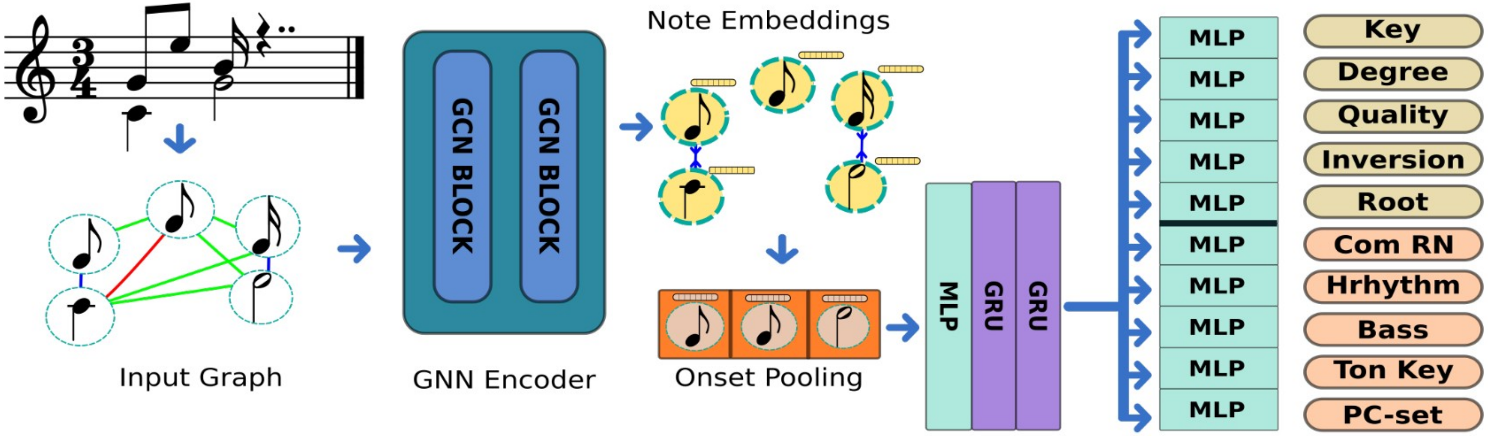
McLeod AP, Rohrmeier MA (2021) A modular system for the harmonic analysis of musical scores using a large vocabulary. In: International Society for Music Information Retrieval Conference. pp 435–442

Roman Numeral Analysis with Graph Neural Networks

- Explicitly represent structure in musical score
- Use graph convolutional neural network to compute embeddings
- Predict features of Roman numeral symbols independently

$$\boxed{\mathrm{I}^{(6)-5}_{(4)-3}/\mathrm{V}}$$

- composition: chord type, inversion, pitch changes
- root position: local key, tonicization



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