When Counterpoint Meets Chinese Folk Melodies

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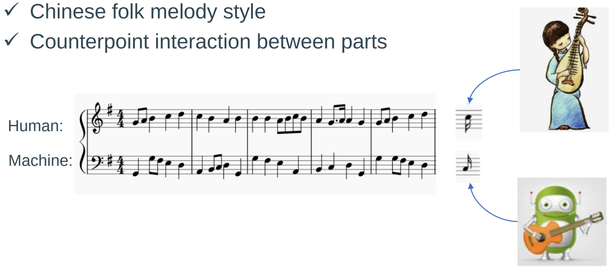
Introduction

Human-machine collaborative duet improvisation.

- ✓ Chinese folk melody style
- ✓ Counterpoint interaction between parts



Task: Incorporating Western counterpoint interactions into Chinese folk melodies for online human-machine collaborative duet improvisation.

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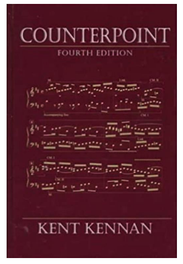


- **Chinese folk melody**: typically presented in a *monophonic* form or with accompaniments that are less melodic.
- **Counterpoint**: mediation of two or more musical voices into a meaningful and pleasing whole.

Challenges

- Out-of-domain data (Chinese folk duets are scarce)

  Monophonic Chinese folk melodies + Bach chorales

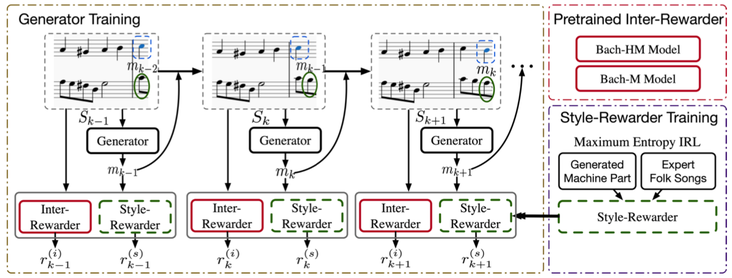
- Counterpoint pattern is coupled with western-music style patterns

  Extract counterpoint interaction pattern & eliminate Western music style

Our Solutions

- Reinforcement Learning → Design task-specific reward functions
- Measure counterpoint interaction using *mutual information*

FolkDuet



Framework of FolkDuet: a Generator and two rewarders

Inter-Rewarder: models the counterpoint interaction in Western music
Style-Rewarder: models the melodic pattern of Chinese folk melodies
The Generator is trained using reinforcement learning with these two rewards.

Rewarders

Inter-Rewarder:
measures the degree of interaction between human and machine parts through a mutual information informed measure.

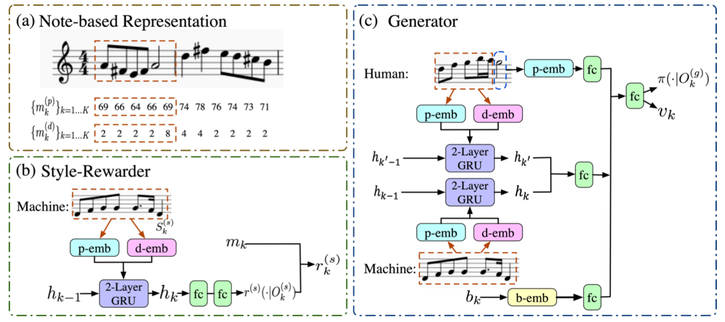
$$I(X,Y) = \sum_{X,Y} P(X,Y)\log\frac{P(X,Y)}{P(X)P(Y)}$$
$$= \sum_{X,Y} P(X,Y)\left[\log P(Y|X) - \log P(Y)\right] \approx \sum_{X_t,Y_t\sim P_{X,Y}} \left[\log P(Y_t|X_t) - \log P(Y_t)\right]$$
$$= \sum_{X_t,Y_t\sim P_{X,Y}} \left[\log \prod_{k=1}^{K^{y_t}} P(y_k^{(t)}|X_t, y_{t<t_k}^{(t)}) \cdot P(y_0^{(t)}|X_t) - \log \prod_{k=1}^{K^{y_t}} P(y_k^{(t)}|y_{t<t_k}^{(t)}) \cdot P(y_0^{(t)})\right]$$
$$= \sum_{X_t,Y_t\sim P_{X,Y}} \sum_{k=1}^{K^{y_t}} \left[\log P(y_k^{(t)}|X_t, y_{t<t_k}^{(t)}) - \log P(y_k^{(t)}|y_{t<t_k}^{(t)})\right] + C(X_t, y_0^{(t)}).$$

$\log p(Machine|Human) - \log p(Machine)$

Style-Rewarder:
Inverse Reinforcement learning (IRL):
learns to infer a reward function underlying the observed expert behavior.

Style-Rewarder is alternatively updated using the maximum entropy inverse reinforcement learning. Its learning objective is to infer the reward function that underlies the demonstrated expert behavior, *i.e.* the Chinese folk melodies.

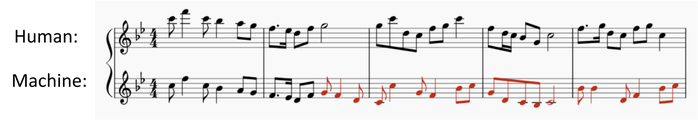
Architectures



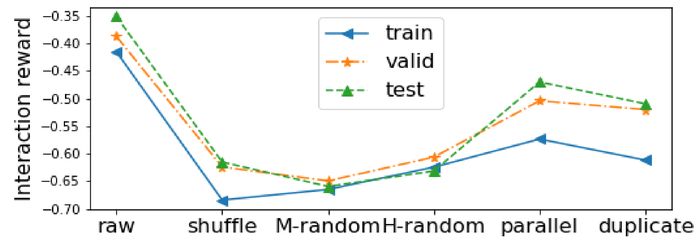
(a) The note-based representation, the network architectures of (b) Style-Rewarder and (c) Generator. p-emb, d-emb and b-emb represent pitch/duration/beat embedding modules, respectively. GRU represents the Gate Recurrent Unit, and fc stands for the fully-connected layer.

Results

Generated Duets



Can interaction reward reflect counterpoint interaction?



original bach's duets	two randomly shuffled parts	random notes in the M part	random notes in the H part	parallel H and M parts	duplicate H and M parts

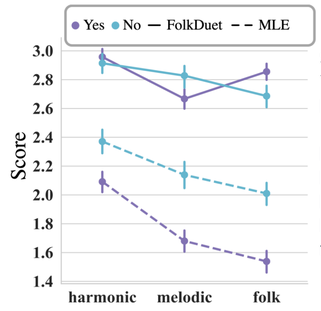
H part and M part are short for human part and machine part respectively.
It shows that this interaction reward achieves the highest score on the original duets.

Objective Evaluation

	PC/bar	PI	IOI	PCH ↓	NLH ↓	key-consist ↑	inter-reward ↑
Dataset	3.90	2.73	2.36	-	-	-	-
MLE	4.21 ± 0.12	$\mathbf{3.02 \pm 0.12}$	2.87 ± 0.10	0.017 ± 0.002	0.036 ± 0.008	0.78 ± 0.01	-0.30 ± 0.02
RL-Duet [27]	3.23 ± 0.01	4.02 ± 0.01	3.64 ± 0.02	0.017 ± 0.001	0.055 ± 0.002	0.71 ± 0.01	-0.50 ± 0.004
FolkDuet	$\mathbf{3.96 \pm 0.12}$	$\mathbf{2.44 \pm 0.14}$	$\mathbf{2.16 \pm 0.10}$	$\mathbf{0.008 \pm 0.001}$	$\mathbf{0.014 \pm 0.004}$	$\mathbf{0.85 \pm 0.01}$	$\mathbf{0.13 \pm 0.03}$

Style: Closer to Chinese folk datasets, in some statistics and distribution distance, e.g. pitch interval (PI), pitch class histogram (PCH).
Counterpoint interaction: Higher key consistency between human and machine parts, higher inter-reward.

Subjective Evaluation



Subjects background:
Yes: have music training/background before
No: have no music training/background before

Evaluation perspectives:
Harmonic: harmonic appealingness of the duets
Melodic: melodic appealingness of the generated part
Folk: prominence of the Chinese folk style of the generated part