Solving Angry Birds with Reinforcement Learning

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Final presentation for INF-PM-FPA Profilmodul Forschungsprojekt Anwendung

Angry Birds - The Game

Angry Birds - The Game

- Artillery game
- Release date: December 2009 (iPhone)
- With $>$ 2 billion downloads in total most popular mainstream game
- Revenue of Rovio Entertainment in 2015: 142 million euro

Principle

- Primary aim: elimination of all pigs
- Secondary aim: maximize points (3 stars)
- Destroyed/damaged objects (ice, wood, stone, pig) and remaining birds = score

Which types of birds do exist?

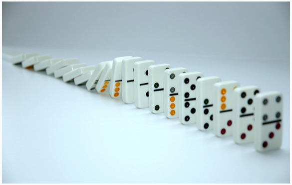
In the first episode “Poached Eggs’ exist:

Picture	Type	Strength	On-Click effect
	Red (Red)	Nothing	Nothing
	Blue (Jim, Jake & Jay)	Ice	Triplication
	Yellow (Chuck)	Wood	Speed-up
	Black (Bomb)	Stone	Explosion
	White (Matilda)	Explosive egg	Drops egg

More types in later episodes …

Why does it matter for AI?

- Predict outcome of physical actions
- No complete knowledge of the world
- Select best action out of $(640 \times 480)^{birds \times taps}$
- $3Birds \rightarrow 1.68 \times 10^{1646}$
- Planning over multiple shots



$\rightarrow$ Competition was born

The competition

- Yearly competition during IJCAI
- Main goal: AI better than Human
- Unknown, newly created levels
- 4 Rounds (Elimination, highest points)
- See more on http://aibirds.org/

Existing Solutions/Approaches

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- DataLab Birds (Data Science Lab Prague, Czech Republic, 1018230 Points)
  - Heuristics for different good actions
- AngryBER (Data Science, Ioannina, Greece, 935330 Points)
  - Machine Learning
  - Calculate expected reward
- Plan A+ (Computer Engineering, Sejong, Korea, 1002380 Points)
  - Two strategy's depending on object breakability
  - Manually tuned parameters (heuristic)
- AngryHEX (974670 Points)
  - ASP Knowledge Base (heuristic)
  - Scene encoding into logic assertions

Our Approach

What do we want to do different?

- Existing solutions (mainly): manual identification of rules or creation of heuristics/scores for good shots
- Our aim: automatic identification of a heuristic which means:
  - Experimental shooting
  - Learn what makes a good combination (planning)
  - Application of learned knowledge in unknown levels

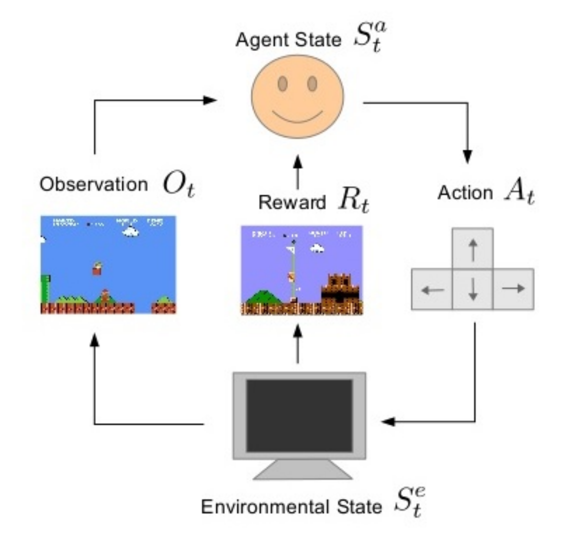
$\rightarrow$ Reinforcement Learning

Reinforcement Learning

Origin

- Field of machine learning
- Behaviorist psychology: animal learning
- Math: optimal control

What is the main principle of Reinforcement Learning?



Q-Learning (1)

Bellmann $\rightarrow$ Value Iteration:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha_t \times \left(r_{t+1} + \gamma \times \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \right)$$

Old Value

Parameter:

- s … state
- a … action

	 12 31	 14 52	 15 72	 15 65
s_0	0	-1	27	3
s_1	5	-1	12	-1
s_2	-1	17	2	-10
s_3	-1	-1	-1	-1
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Learning rate

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Reward

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Discount factor

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Estimate of optimal future value

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Q-Learning (2) - Exploration rate

Law of Effect aka Trial & Error with parameter ε (exploration rate)

```
public Action getNextAction() {
        int randomValue = randomGenerator.nextInt(100);
        Action action;
        if (randomValue < explorationRate * 100) {
            action = qValuesDAO.getRandomAction();
        } else {
            action = qValuesDAO.getBestAction();
            }
        return action;
}
```

Q-Learning (3) - Delayed feedback

- Positive reward only on last shot
- First action affected after n games for n birds

Labyrint Example

- 5 x 5 World
- Possible Actions: Up, Right, Down, Left
- Rewards per move:
  - Green tile: +1
  - Red tile: -1
  - Default tile: -0.05

Live

Our Model for Angry Birds

- State: Serialized screenshot with
  - rounded coordinates
  - object-type
  - object-shape
- Action: Shoot on center of an object (Limitation: object direct reachable)
- Reward: Score after successful finishing the level

State: RedBird 19 32 Rect … Wood 59 35 Rect Pig 54 29 Rect

Action: Wood 49 35 Rect Wood 54 31 Rect …

Observation of pure Reinforcement Learning Approach

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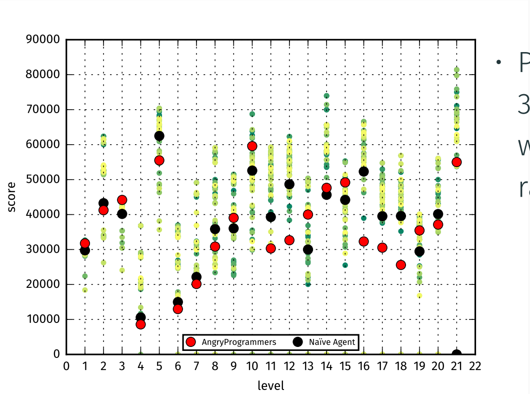

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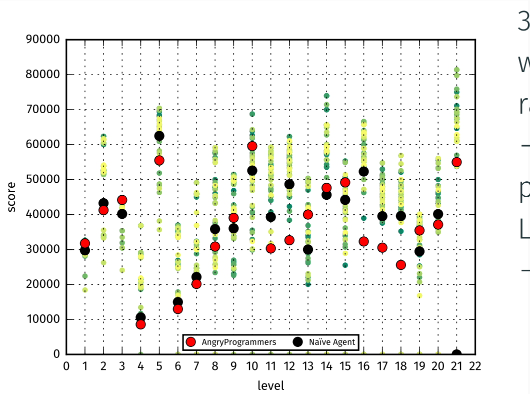

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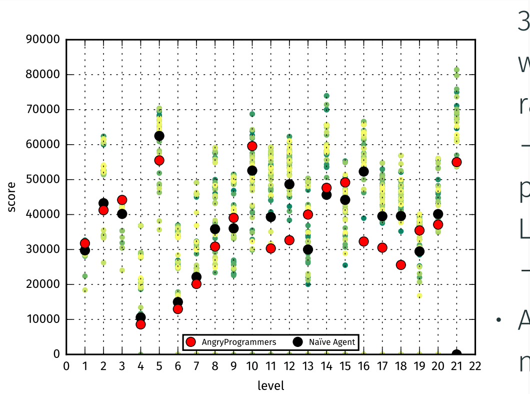

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- Achieved scores similar to naïve agent
  → suggests that nothing was learned

Encountered practical Problems while implementing the Theory

Encountered Problems

Game is implemented as closed source Chrome plugin

- Chrome plugin and screenshot analysis needs lots of resources

  → couldn’t run more than 4 Chrome processes in parallel on a ZIH VM with 16 cores and 32GB ram

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- Not possible to create new levels → overfitting!

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→ increases exponentially search space

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New approach

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- Instead of proposing all possible target objects, low/high trajectories and tap time a preselection of most promising targets
- Reinforcement learning shall again select, based on the current state, which preselected action to take
- Drawback: learned strategy is limited by preselected actions
  → no totally new strategies

Hybrid approach: Reinforcement Learning and Heuristics

Heuristics used for preselection of possible targets:

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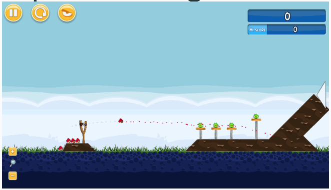

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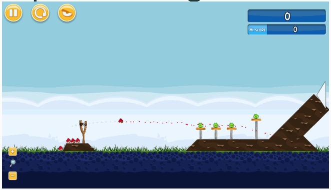

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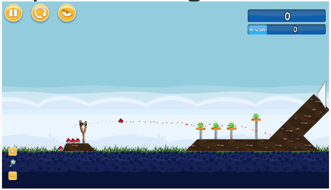

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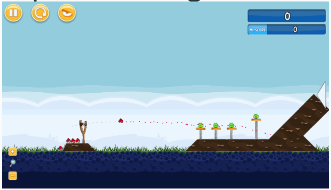

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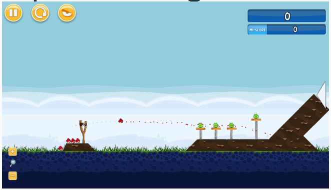

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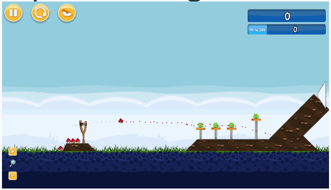

- Score depending on following factors:
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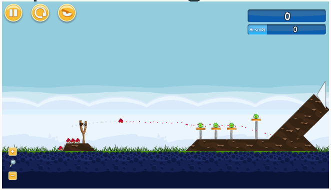

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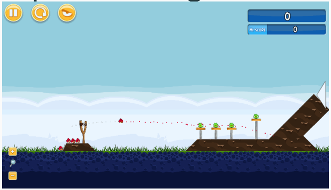

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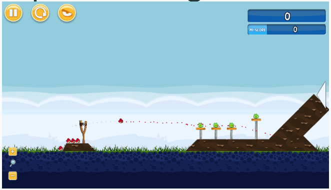

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    - Material
    - Orientation
    - Distance to pigs

Observation again

Observation of Reinforcement Learning and Heuristic

- Played levels after 2 weeks: 5172

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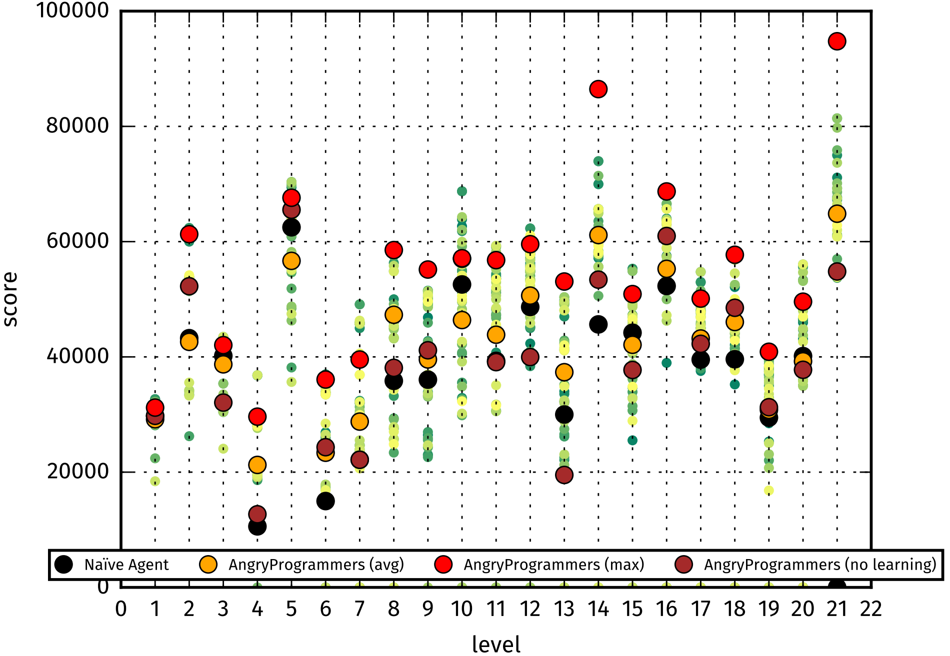
- 1–2 tries needed to solve first level, later level needed comparably much more tries


score
level
Naïve Agent
AngryProgrammers (avg)
AngryProgrammers (max)
AngryProgrammers (no learning)
0
20000
40000
60000
80000
100000
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22

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- But: good results aren't reproducible yet because the really good shots haven't been remembered
  → delayed feedback in Q-learning
- for competition the overfitting still needs to be checked
- not yet implemented strategy for solving unknown level in competition modus

Outlook

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- Reimplement the game in a more machine learning friendly way
  - API to get current objects
  - Direct output of computed resulted state after shooting an object (no useless wait for pretty animation to finish)
- Can't discourage to not use Reinforcement Learning, result of second approach looked promising
  → leads to speculation that first approach probably would have worked with more iterations

Questions?

Level 14

Level 14

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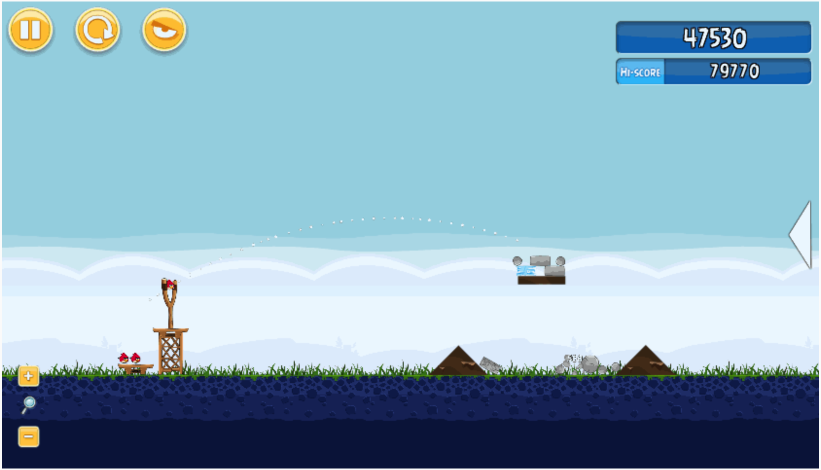

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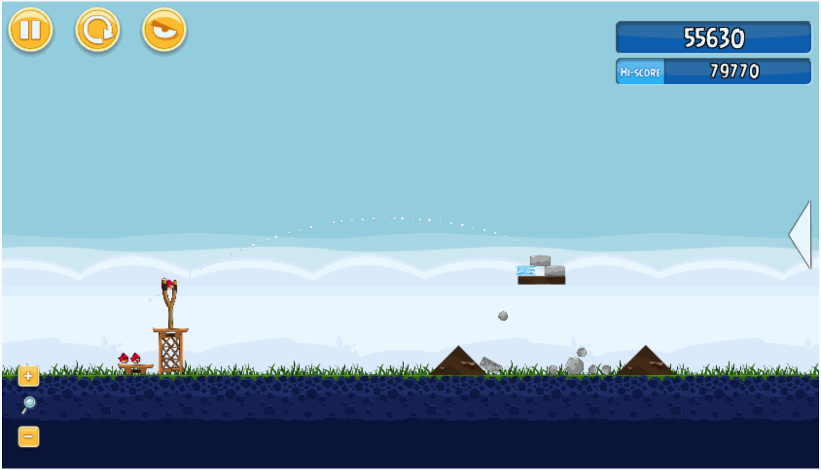

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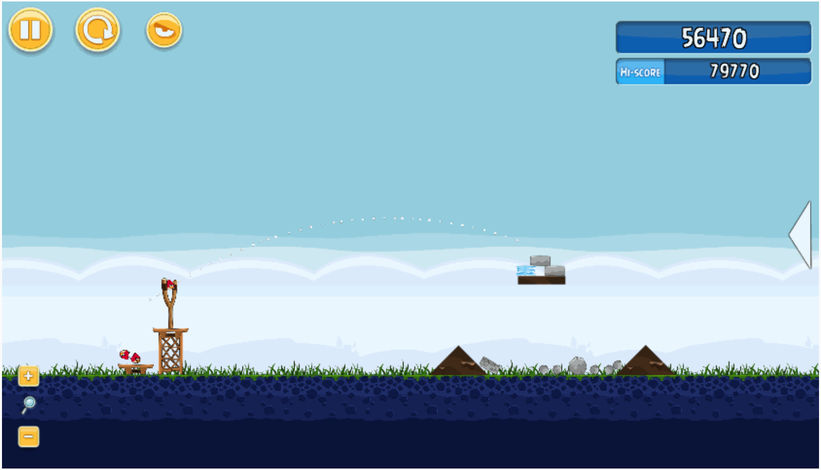

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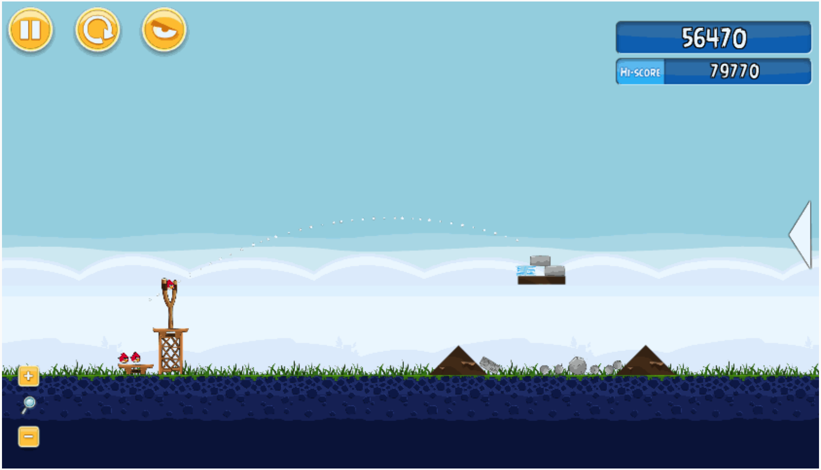

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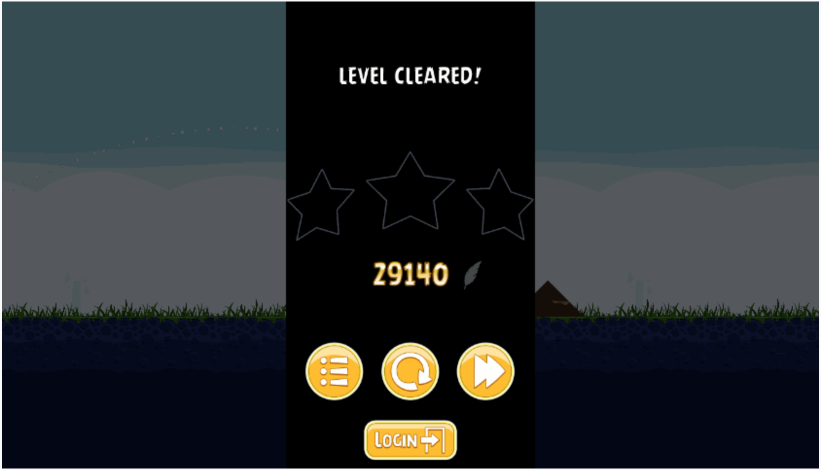

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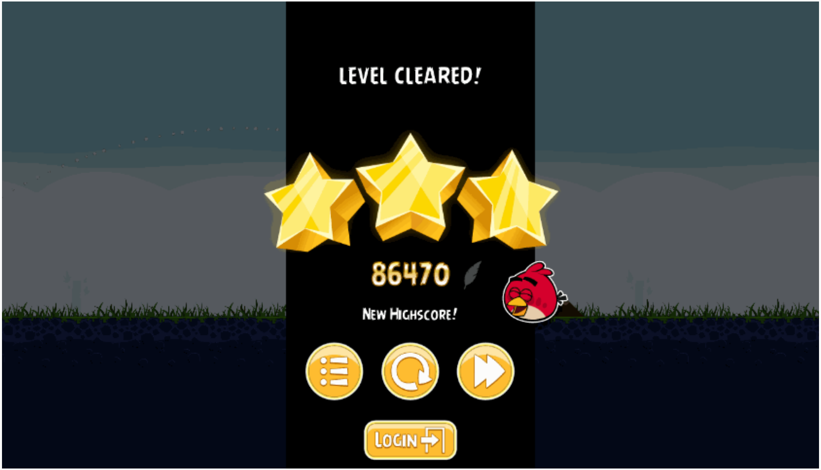

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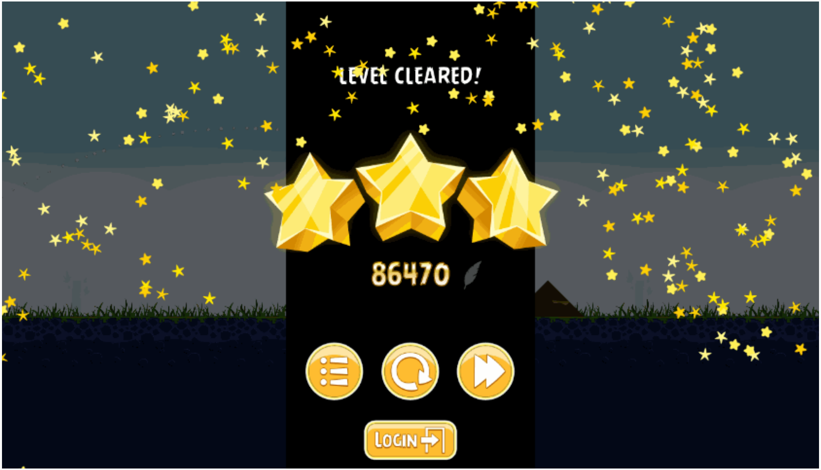

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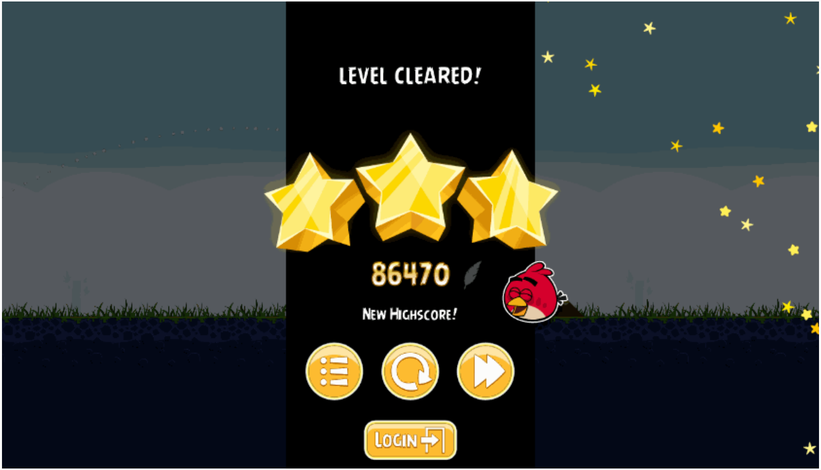

Level 21

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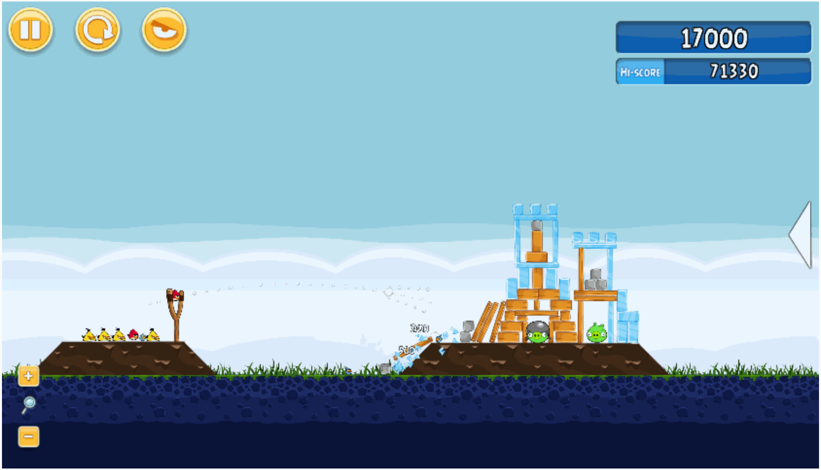

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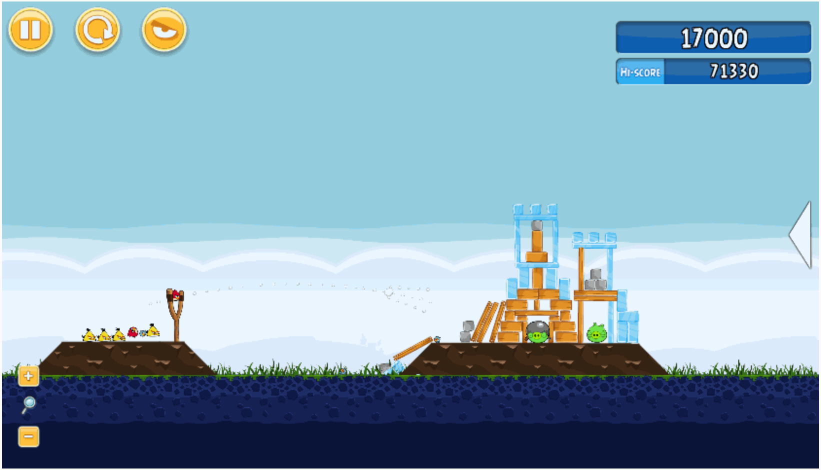

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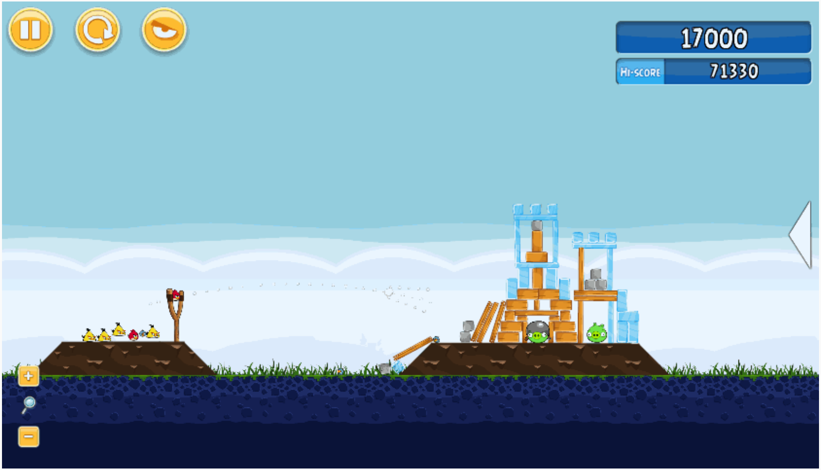
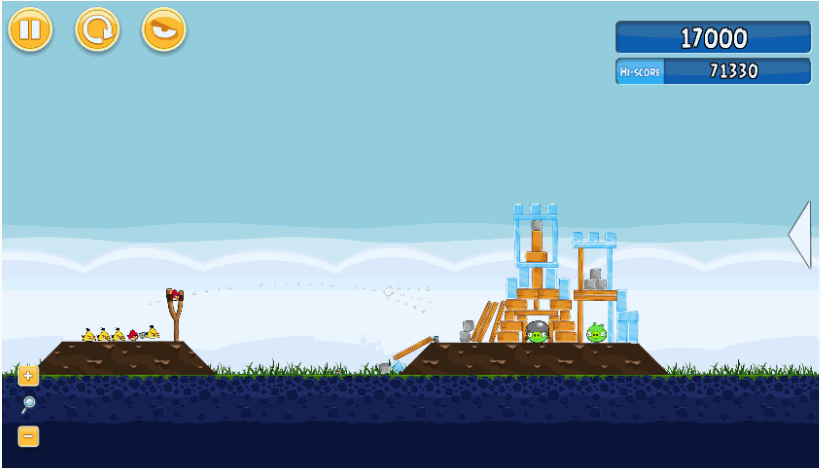


Level 21



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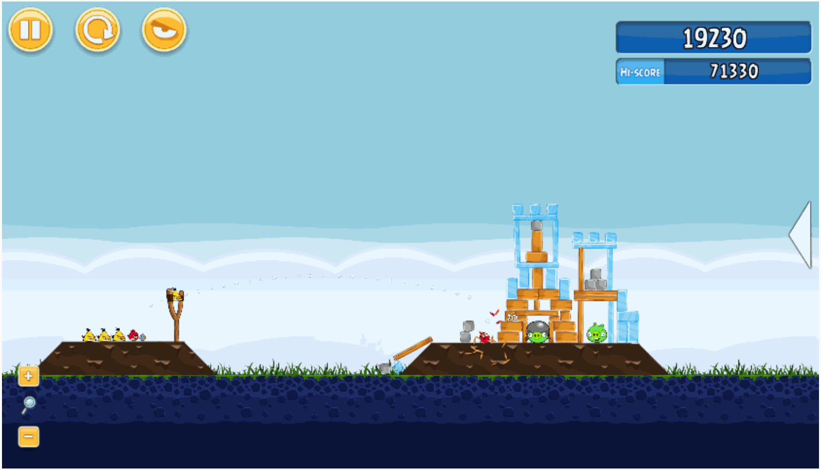

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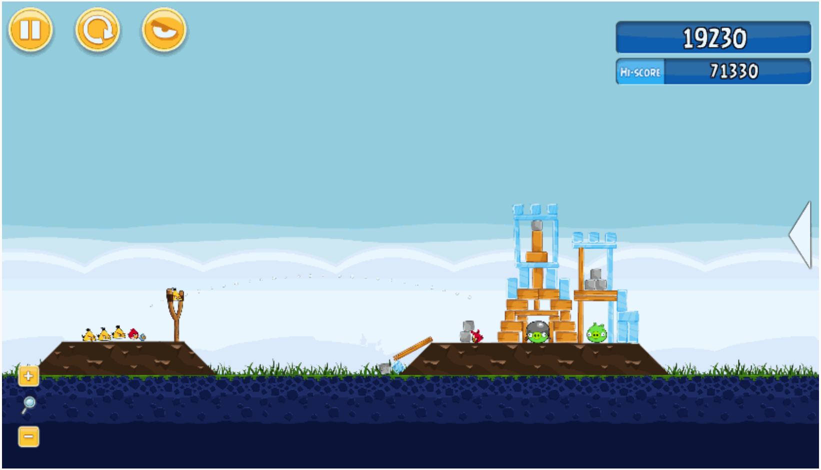

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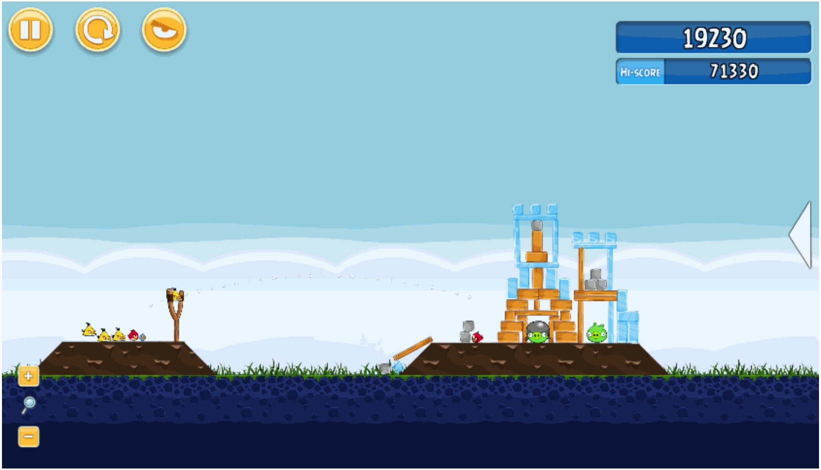

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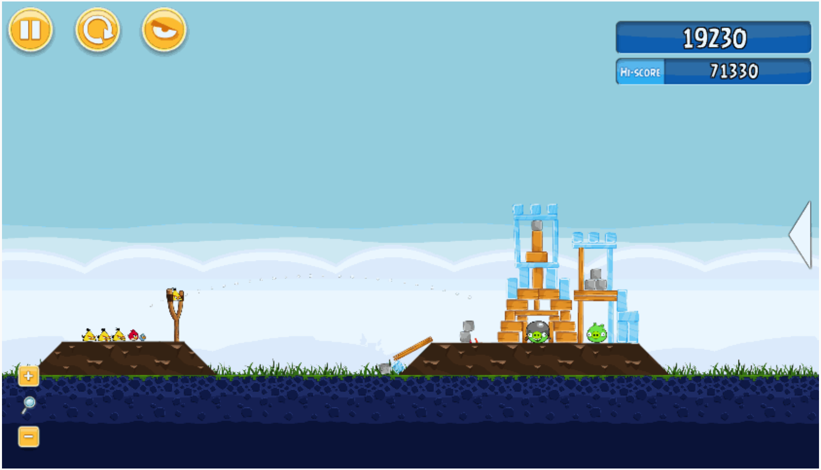

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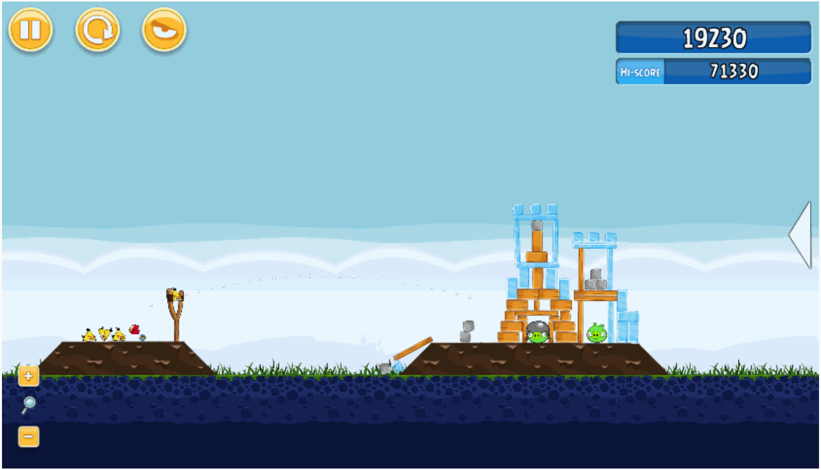

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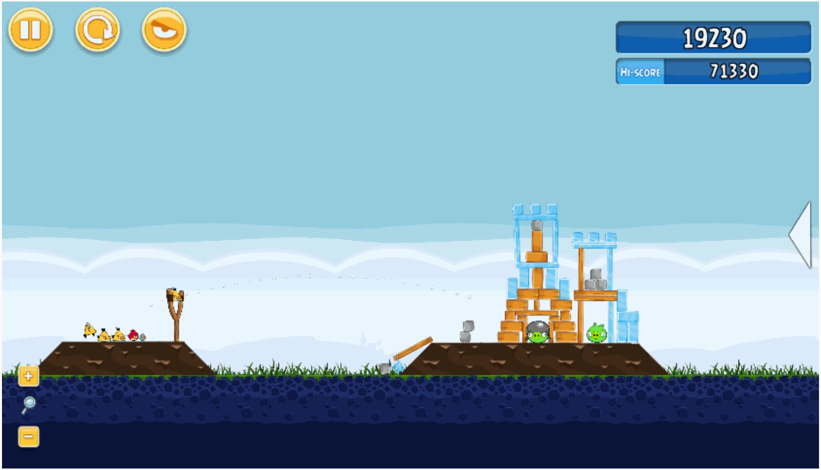

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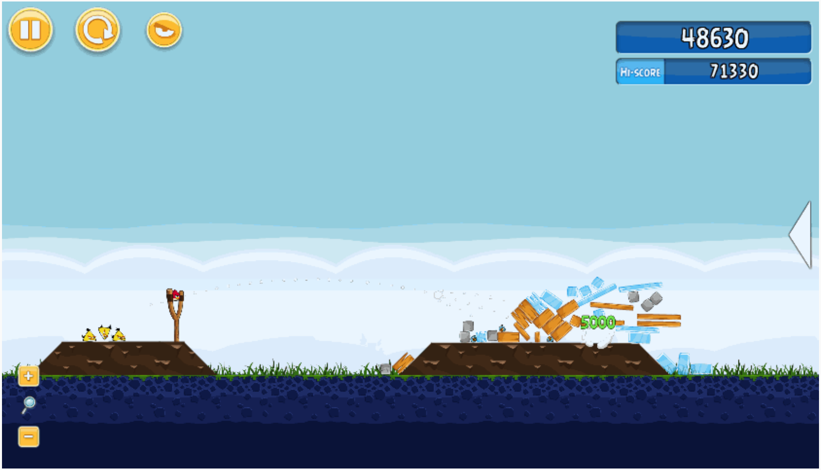

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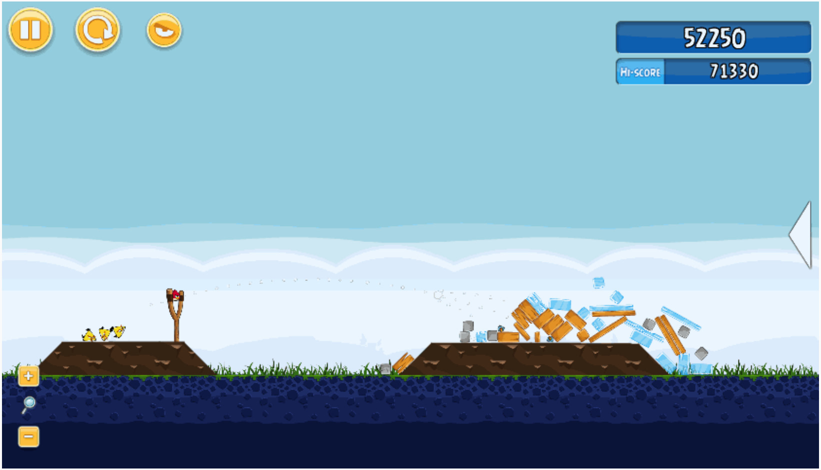

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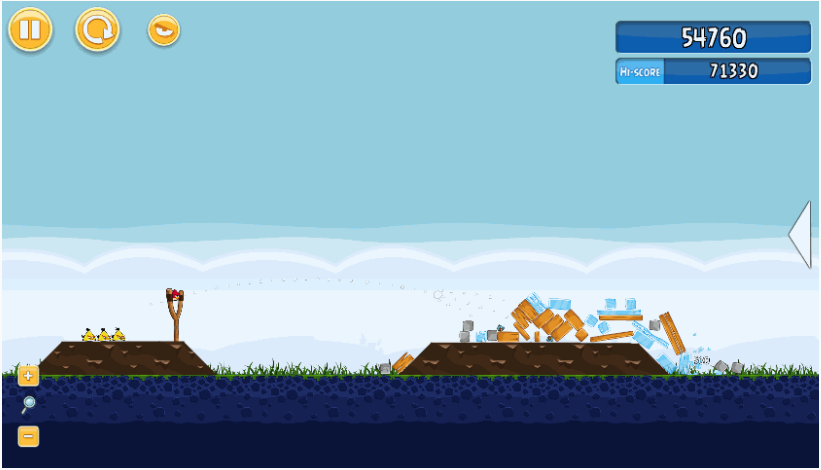

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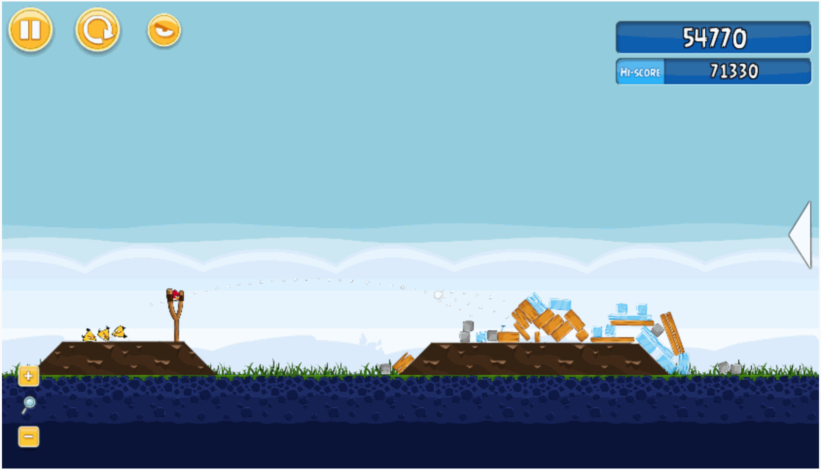

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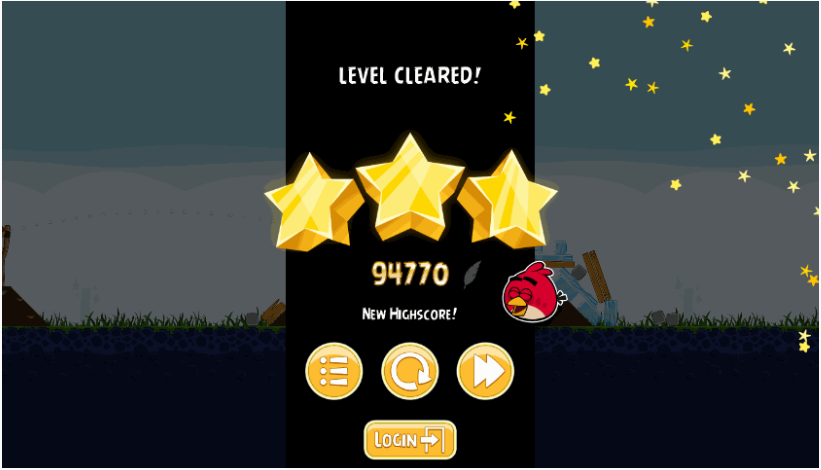

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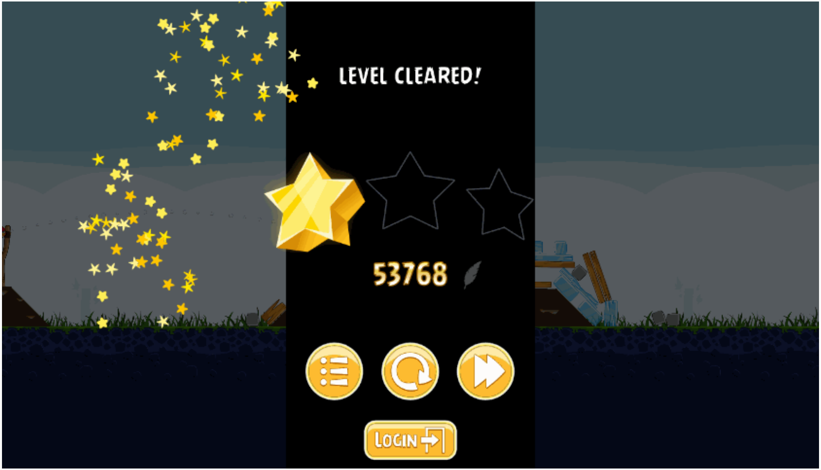

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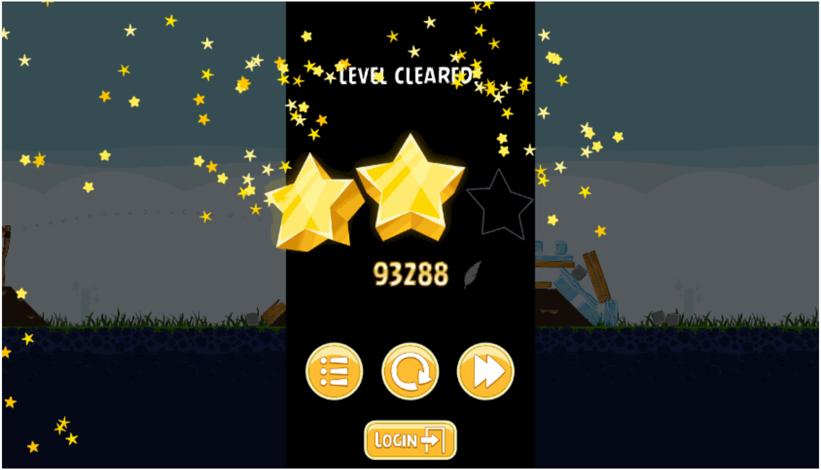

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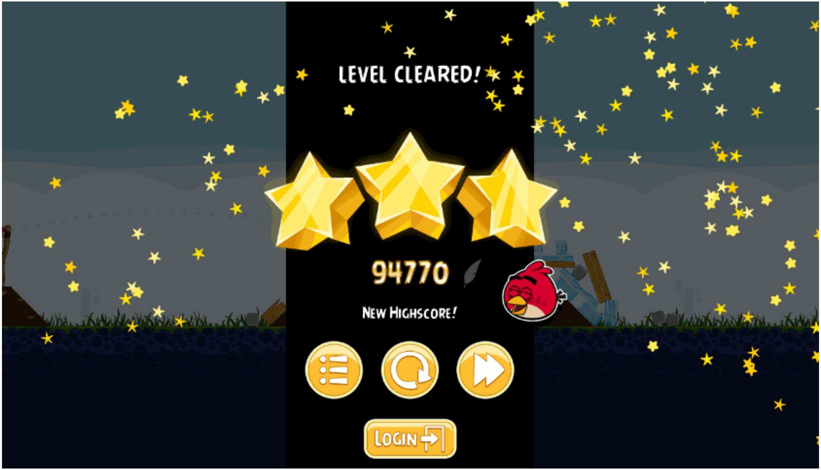

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